Quality monitoring of complex manufacturing systems on the basis of model driven approach

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Abstract. Monitoring of complex processes faces several challenges mainly due to the lack of relevant sensory information or insufficient elaborated decision-making strategies. These challenges motivate researchers to adopt complex data processing and analysis in order to improve the process representation. This paper presents the development and implementation of quality monitoring framework based on a model-driven approach using embedded artificial intelligence strategies. In this work, the strategies are applied to the supervision of a microfabrication process aiming at showing the great performance of the framework in a very complex system in the manufacturing sector. The procedure involves two methods for modelling a representative quality variable, such as surface roughness. Firstly, the hybrid incremental modelling strategy is applied. Secondly, a generalized fuzzy clustering c-means method is developed. Finally, a comparative study of the behavior of the two models for predicting a quality indicator, represented by surface roughness of manufactured components, is presented for specific manufacturing process. The manufactured part used in this study is a critical structural aerospace component. In addition, the validation and testing are performed at laboratory and industrial levels, demonstrating proper real-time operation for non-linear processes with relatively fast dynamics. The results of this study are very promising in terms of computational efficiency and transfer of knowledge to manufacturing industry.

Keywords: quality monitoring; model-driven; artificial intelligence-based models; surface roughness; fuzzy clustering; manufacturing; embedded systems; hybrid incremental model

1. Introduction

Nowadays, the trend for deploying real-time embedded systems aims towards distributed manner (Iarovyi *et al*. 2015). The distribution and parallelism in the design of real-time embedded systems increase engineering challenges and require a new methodological system based on middleware Mohammed *et al*. (2018a). With this strategy, Brinkschulte *et al*. (2001) developed a middleware that supports the design of heterogeneous distributed real-time systems and allows the use of small microcontrollers as calculation nodes.

Some systems and architectures for real time process monitoring have been designed and implemented in embedded platforms and frameworks such as those reported in AitMou *et al*. (2018) and Salman *et al*. (2019). However, some of them have opted for running on PCs (Mohammed *et al*. 2018b). These systems have begun to evolve, for example, based on FPGA (Field Programmable Gate Array) solutions capable of producing the same results but with lower computational costs (Hashmi *et al*. 2014, Humphreys *et al*. 2014) and with a reduction of energy consumption (Castaño *et al*. 2010). Due to the cost-effectiveness of the new generation of devices powered by microcontrollers, it is economically feasible to embed a number of these devices into a machine placing the information sources near to the process to form a network of distributed smart sensors (Mönks *et al*. 2015).

Machine tools equipped with Computerized Numerical Control (CNC) are the cornerstones of the manufacturing industry (Guerra *et al*. 2019). Therefore, machining processes are the most important operations. Milling, drilling and turning cover a wide variety of different operations and machines on scales from micro scale (0.01-0.5 mm of cutting tool diameter) up to macro scale (> 0.5 mm of cutting tools diameter). These processes are essential for producing high quality parts with complex shapes including ramps, contours, pocket, holes, etc., at high removal material rate. Nowadays, several manufacturing industries in aeronautics, health and space sectors demand high productivity with very high quality of the products. The quality monitoring of processes and components has been centered on tool wear and breakage, surface roughness, chattering and vibrations (Ramezani *et al*. 2019), among others (Park *et al*. 2018).

Some complex manufacturing processes, such as micro-mechanical machining operations, capable of component

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miniaturization, are highly demanded especially in applications related to medical instrumentation, aerospace engineering and computer manufacturing, among others (Venkatesh *et al*. 2017). More acute difficulties arise due to the increased accuracy of manufactured parts and the decrease in overall part dimensions and cutting tool diameters. Regarding monitoring, it is nearly impossible for expert operators to monitor micro-machining operations by means of visual inspection or audible signals alone due to the dimensions of tools, chips, burrs and the amount of lubricant that is used (Kiswanto *et al*. 2014. Muhammad *et al*. 2018, Ranjan *et al*. 2020, Villalonga *et al*. 2020). Moreover, the mechanical, thermal and electrical properties of certain strategic materials such as tungsten-copper alloys raise other problems, such as abrasive wear mechanism, deterioration in tool geometry, deterioration of surface quality and burr formation (Beruvides *et al*. 2013, Erçetin *et al*. 2018).

One way to address some scientific and technical challenges that arise in micro-milling operations is by designing real-time monitoring systems that employs special sensors. The foundation of any reliable monitoring system is necessarily comprise of an efficient and if possible low-cost sensorial system with fast signal processing methods and low-cost computational strategies that are capable of relating measured signals with relevant information on the process status (Beruvides *et al*. 2014a, b, c). A multi-objective optimization strategy to integrate sensors data in efficient and simple computational procedure based on improved cross-entropy method is proposed by (Haber *et al*. 2017). More recently and focused on micro-scale processes, a system has been developed for tool condition monitoring in micro-milling processes by (Jemielniak *et al*. 2008).

Even though the use of multiple sensors to monitor micro-milling contributes to the robustness and reliability of the process (Xu *et al*. 2019), their use also increases cost, wiring and computational processing. Nevertheless, the literature has also reported recent research on tool condition monitoring in milling processes by means of a single sensor.

For example, interesting results have been reported on a single sensor that measures the current consumed by the feed drive (Sevilla-Camacho *et al*. 2011, Gao 2012) or by an acoustic emission sensor (Yen *et al*. 2013). However, a tradeoff between the amount of sensory information, sensitivity at high frequencies and cost in relation to other sensors (acoustic emission, cutting force, etc.) is hardly straightforward. The unique characteristics of vibration signals and vibration sensors should therefore be explored and studied for the monitoring of micro-milling systems (Huang *et al*. 2008).

Therefore, from the best of authors' knowledge, the main contribution of this work is a method for developing and implementing a distributed, modular and network-based framework with embedded model-driven strategies for real-time quality monitoring of processes, specifically micro-scale machining processes. Two AI-based strategies are studied and applied for monitoring the surface roughness by predictive models as follows: The hybrid incremental modelling with optimal parameters from the Simulated Annealing method (HIM-SA), and a Generalized Fuzzy Clustering C-Means method which parameters fitted by a Backpropagation error Procedure (GFCM-BP). In addition, the proposed method also takes into account the integration other essential procedures such cutting states and early tool breakage detection. The embedded model-driven approach is very challenging from computational viewpoint in real-time adjustment and synchronization. The complexity of manufacturing processes and the cross-correlation of variables influencing on surface quality imply that these methods should run simultaneously in real time with parallel threads with different cycle time and priority (Lee *et al*. 2018).

For a better understanding, this paper is organized as follows. After this introduction, a review of the state-of-art considering some works related to this research is presented.

Later, the implementation, both software and hardware, of the system for intelligent quality monitoring is described. Next, the two computational intelligence methods for surface roughness modelling are presented in section 4. Then, the suitability study on integrating and real-time running of these methods in parallel is carried out and presented. An industrial application in manufacturing company with the goal of experimentally validating the proposed system is also presented. Finally, some conclusions and future research steps are addressed.

2. Related works

Up to date, a wide range of conventional methods (so called to differentiate them from intelligent techniques) has been used for the design of monitoring and supervision systems (Yi *et al*. 2015). The interface and final result of the monitoring strategy and quality control procedure can be delivered directly or modified by embedded algorithms that convert a high volume of real time data into useful information or recommendation in a more precise and understandable format by the operator (Beruvides *et al*. 2014a, b, c).

A typical embedded system is usually organized and structured in modules for embedded algorithms, a module for recording states, a module for data storage or database and modules for human-machine interaction and user interface among others (Lim 2019). The latter arises due to the nature of embedded systems that require computer components to interact with the external world, in what is called Human-Machine Interaction (HMI) (Lipiński and Majewski 2015). Therefore, real-time and embedded systems have a number of significant characteristics. The reader may find further information in Reichenbach *et al*. (2014).

Complex processes such as micro-scale manufacturing processes are characterized by time variant and non-linear behavior, producing different undesirable results and unavoidable operation states of the system. The influence of disturbances is one of the main disadvantages to yield a controlled behavior of the system in an optimal operating state. Therefore, AI-based real-time monitoring procedures

Table 1 AI-based strategies for quality monitoring and real-time systems

Technique and application	Author
Probabilistic computing, bayesian networks Modelling and monitoring	(Ma *et al*. 2019, Wang *et al*. 2019, Constantinou *et al*. 2016, Zhang *et al*. 2019)
Artificial Neural Networks (ANN) Modelling and monitoring	(Hoang and Kang 2019, Stetco *et al*. 2019, Yu and Xi 2009, Onat and Gul 2018, Mosavi *et al*. 2018)
Fuzzy Logic (FL) Modelling and monitoring	(Zoroglu and Turkeli 2016)
Hybrid neuro-fuzzy systems. Modelling and monitoring.	(Choi *et al*. 2016, Kothamasu and Huang 2007, Waewsak *et al*. 2010, Kamel *et al*. 2015, Zarkogianni *et al*. 2015, Dzakpasu *et al*. 2015, Azmi 2015, Gajate *et al*. 2010)
Evolutionary algorithms, hybridization. Modelling and monitoring	(Di Francescomarino *et al*. 2018, Li *et al*. 2010, Beruvides *et al*. 2017)
State machines and decision-making. Modelling	(Foukarakis *et al*. 2014)
Smart embedded system (i.e., ANN, FL, among others). Supervision	(Silva Junior *et al*. 2015, Kryjak *et al*. 2018, La Fe-Perdomo *et al*. 2019)
Real-time and runtime architectures. Supervision	(Treutterer *et al*. 2014, Haber *et al*. 2015, Flouri *et al*. 2012)

Table 2 AI techniques in the supervision of micro manufacturing processes

Modelling, monitoring and supervision	Related to	Authors
ANFIS model for microplate and micromachining by EDM	Surface quality	(Suganthi *et al*. 2013)
ANFIS model for micro turning	Tool and chip	(Palani *et al*. 2013)
Artificial bee colonies for optimization of electro-chemical micromachining processes	Tool, surface and chip	(Samanta and Chakraborty 2011)
ANN propagation backward for prediction of EDM process	Hole quality	(Rajesh Kumar *et al*. 2014)
Fuzzy logic for optimizing the response of multiple processes in electro-chemical micromachining	Chip and tolerance	(Alakesh 2012)
Fuzzy-genetic system for modelling micro drilling process	Thrust force	(Beruvides *et al*. 2014a, b, c)
Estimated distribution functions for optimizing micro drilling process	Thrust force	(Beruvides *et al*. 2016b)
ANN to predict thrust force micro milling processes	Burr	(Zhu *et al*. 2011)

and computational architectures arise as an attempt to guarantee the quality of the system's response, in the face of any adverse situation or disturbances. However, sensor data measurement and processing of useful knowledge is a complex task since large amount of raw data from the sensors should be analyzed in real time and constantly updated (Fiol-Roig 2004). Accordingly, if the required time response of tasks and methods for quality monitoring is very challenging, a fast real-time updating of the information is required. In addition, high quality information from real time sensor data is needed. Therefore, there is clear tendency towards the use of alternative strategies such as those described below and reported in the literature. Artificial intelligence-based methods become an alternative to emulate the behavior of complex processes that require an accurate and complex knowledge representation (Turing 2009).

Table 1 summarizes some of the relevant AI strategies, in which several sensors are applied to monitoring some complex processes, mainly in real-time. From this analysis and taken into account common characteristics, some new potential applications can emerge. However, the results of applying traditional strategies have not met some expectations but instead have generated many undesired results and false alarms since many times they are supported on exact mathematical models or linear models of the process such as differential equations, transfer functions and state equations.

To further illustrate applications of AI techniques for monitoring micro manufacturing processes, Table 2 shows some reports specifying the type of microfabrication process and the specific modelled or monitored variable. In summary, the review is focused on computational intelligence techniques by analyzing its evolution from its beginnings to current trends. For example, in fuzzy logic-based approaches, the focus is on fuzzy clustering methods because of the worldwide and successful applications. Additionally, the review also considers some meta-heuristic search methods, such as simulated annealing and cross entropy methods essential for tuning some algorithms. The parametrization of AI-based methods is the main bottleneck for industrialization quality monitoring and control strategies. Other strategies have not been considered in this study due to the need of deterministic real time require-

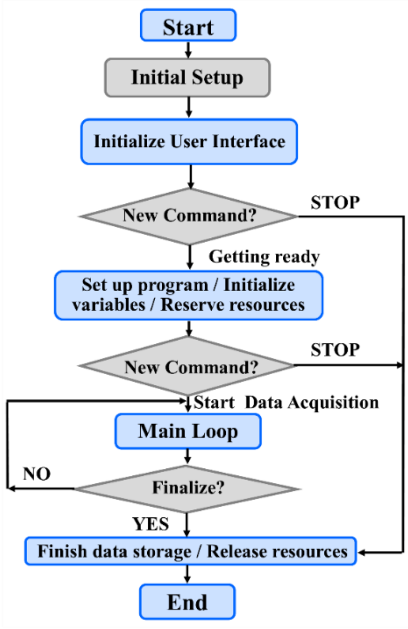


Fig. 1 Flow chart of the main program of the monitoring system

ments. For this reason, methods and computational architectures based on edge computing emerges as a potential solution with connectivity and distributed processing capabilities.

3. Framework description for intelligent monitoring

As it was already mentioned above, the main goal of this work is to monitor the final quality of the manufactured components or parts by estimating surface roughness from vibration signals and cutting parameters information. Surface roughness is an essential feature in quality control defined by the deviation in the direction of the normal vector of a real surface from its ideal form. Because the roughness measurement is an offline and post process procedure, being able to estimate this value online brings a series of benefits in terms of time and cost reduction in manufacturing lines, energy efficiency, unnecessary wear of tools and machines, etc.

In addition, the challenge is to integrate AI-based model for predicting the surface roughness with other strategies such as cutting states detection and tool breakage prediction. The adjustment and synchronization of these strategies is not straightforward because they are cross-correlated influencing on surface quality and should run simultaneously in real time with parallel threads. For example, early tool breakage detection is a very fast task (miliseconds in micro-scale mechanical machining) that is essential to surface quality and to avoid part damage and re-manufacturing.

Nowadays, there is not precise mathematical framework to estimate the surface roughness exactly and Artificial Intelligence has demonstrated to be an alternative tool for intelligent monitoring. In this section, the design and implementation of an intelligent monitoring system and the

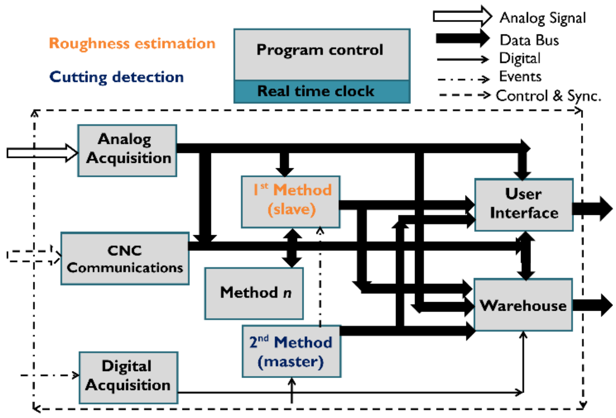


Fig. 2 Execution threads in parallel of the main loop

corresponding framework, software and hardware, for quality control is proposed.

3.1 Software architecture

For the realization of the system, an application framework is developed in G-code and in high-level C language using the LabVIEW® 2017 graphic environment. The main program is implemented in the graphic environment, which includes the user interface, the signal acquisition from sensors via PXI-6259 acquisition card, the processing of data to feed the socket modules of decisions and estimation, and other associated tasks, such as reading vibration signals, screen refresh, store on disk and communication with Computerized Numerical Control (CNC) server. It is also important to highlight that the modules for decision-making on the cutting state and for the estimation of surface roughness have been developed in language C (see sections 3.1.1 and 3.1.2).

The main program is organized in a structure stacked in frames. Each frame contains a functional group of actions, and the frames are executed successively in a predefined order. After the last execution, the system returns to the beginning. In this way, the application runs continuously, allowing monitoring long micromachining operations.

The main operating core of the program consists of a series of loops or threads that run in parallel (see Fig. 1). Each loop performs a different function, with an associated clock frequency according to the operations it performs. Information between loops is transmitted using FIFO (First In First Out) stack. This technology of data transfer between threads, allows access within a loop to the information generated in another, without loss of information and deterministically.

Fig. 2 shows the main monitoring task, which constitutes the main operating core of the program and consists of a series of loops or threads running in parallel. The different wires are interconnected, either through data buses, digital signals, events and control and synchronization signals. There is a thread in charge of program control and synchronization of the other threads, which includes the real-time clock. On the left side, we find the input wires that perform the acquisition and capture of data, both digital and analog signals. Then the methods,

Table 3 Time table of the threads

Thread of execution	Priority	Cycle time (x = 50 µs)
Detection of cutting states	1500	5x
Reading vibration signals	100	100x
Roughness estimation	100	1000x
Screen refresh	50	10000x
Store on disk	25	1000x
End monitoring	100	20000x
Communication with CNC server	100	300x

which are located at the center, are activated by event from other methods. In the particular case developed in this work, the methods that have been embedded in the software platform are the surface roughness estimation and cutting detection. Finally, user interface and database present the information to the user or persists the knowledge for future utilization.

Table 3 lists the different threads of the main program. Its relative priority is detailed as well as the execution time of the cycle. The priority is used by the operating system when there are conflicting tasks in order to decide which thread runs first and which one is waiting to continue its execution. Cycle times are referred to a common time base of 50 microseconds and therefore, times in the table are multiples of this time base.

In addition, it is important to highlight that functions implementing the model-based monitoring framework are encapsulated in Dynamic Link Libraries (DLL). The implementation of the embedded methods, model-based roughness estimation and the cutting states detection, will be as computationally efficient as possible in order to execute the framework in real-time. The two methods to be embedded are the following.

3.1.1 Method for cutting monitoring and breakage detection in the micromachining process

The monitoring of the cutting states and tool breakage detection constitutes one of the execution threads of the monitoring system. The design and implementation of the smart sensor is reported in Castaño *et al*. (2015a, 2017). This task is configured to have the highest priority in the whole system When the high precision requirements for monitoring cutting operations are specified. In addition, this enables determining precisely the changes that occur between the different states of the cutting operation and it will be enough accurate when each change of the average roughness value per operation is estimated.

3.1.2 Method for predicting surface roughness

The module for predicting surface roughness in micro milling operations is included in the monitoring system. During this loop, inputs that are defined for the roughness model are calculated (see Section 3) and the call to the function embedded in the DLL library is made. The model parameters are previously loaded, before the beginning of the state monitoring of the cutting operations.

From the value estimated by the roughness model, the estimation error is calculated according to the average percentage error obtained during the roughness model training. This data is part of the configuration of the monitoring prototype. Both the estimated value and the error in the estimation are displayed in the user interface and stored on disk in case a subsequent analysis is necessary.

3.2 Hardware implementation

The hardware setting of the system for quality monitoring is equipped with the following devices, as shown in Fig. 3:

• An industrial PC connected to the intranet of the

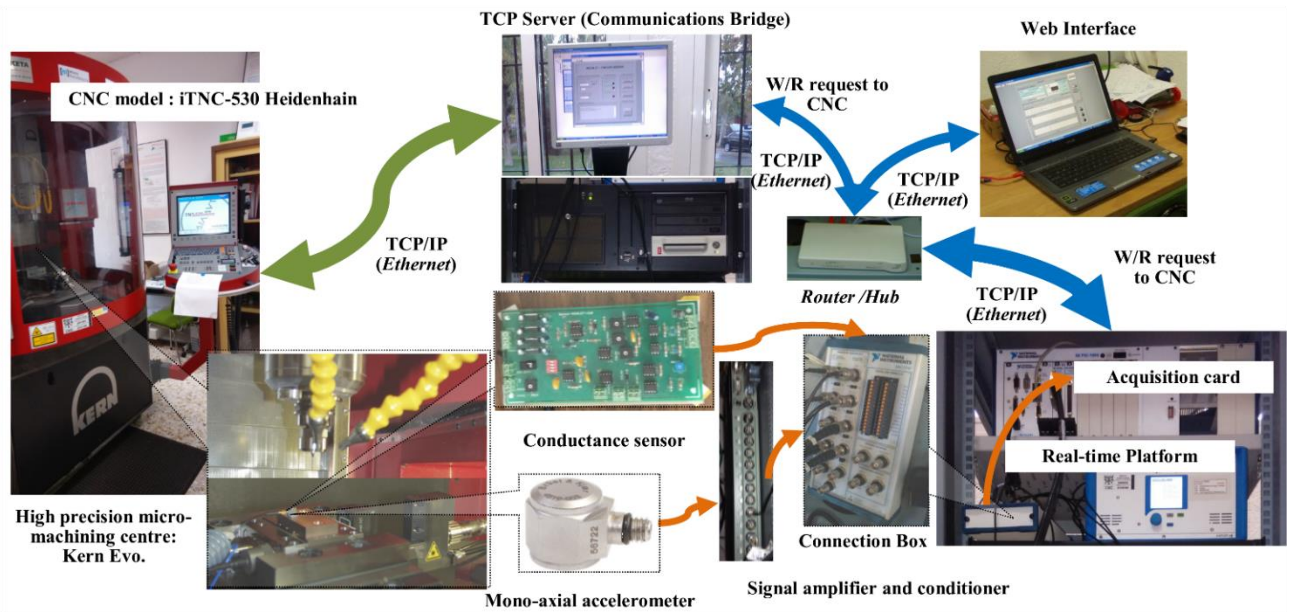


Fig. 3 Global vision of the framework developed for real-time monitoring of complex processes

machine tool via Ethernet is responsible for executing real-time monitoring programs. It is a state-of-the-art commercial platform, namely the national instrument PXI-1050 platform with PXI-8187 processor.

• A PXI-6259 data acquisition card is responsible for converting the analog signals of the sensors into digital signals.

• The sensor is connected through the signal conditioner PZT482A22 via analog inputs to DAQ card that is responsible for preparing the signals of the vibrations.

• The physical means of joining the output of the feeders and adapters of the sensors is through the BNC-2110 junction box.

• A Kern Evo high-precision micromachining center, which is equipped with a computer numerical control (CNC) iTNC530 from Heidenhain.

• The two sensors recommended to meet the criteria of minimum possible sensory information: the vibration sensor for the Z axis (Bruel and Kjaer 4519-003 mono-axial accelerometer model) and the conductance smart sensor.

4. Embedded computational intelligence methods

For the design of the experimental models of representative variables of the microfabrication process, a proposal that consists of two AI-based modelling strategies have been chosen in advance precisely because they have characteristics and have good behavior for the problems that are considered in this work. In this particular implementation, the representative variable to be estimated is surface roughness that is a typical measurement in order to ensure the quality of the manufactured parts. The surface roughness is selected and specifically the average of the roughness profile, *Ra*, being one of the most used industrial indicators to evaluate the surface quality of the microfabrication process (Beruvides *et al*. 2017). The vibration signal from Z-axis accelerometer and the feed-per-tooth value are used as input variables.

The first strategy of the study is the Hybrid Incremental Modeling (HIM) technique and in particular, as local model, a *k*-NN clustering technique is selected as the local model. The second method is a Generalized Fuzzy clustering algorithm C-Means (GFCM) with a neuro-fuzzy system. The proposal of both AI-based modelling strategies is shown in Fig. 4.

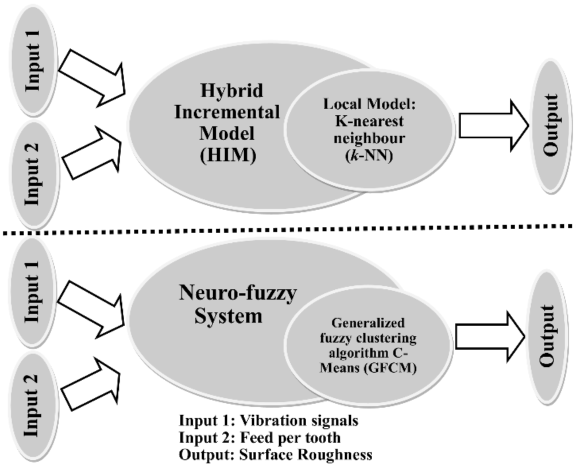


Fig. 4 The proposal of two AI-based modelling strategies for quality monitoring

4.1 Theoretical foundation

In this section, the theoretical foundation of both strategies is presented. For HIM, this theoretical foundation can be found in the following previous works (Penedo *et al*. 2012, Beruvides *et al*. 2016a).

For GFCM, it is important to highlight that before all the possible variants in the literature on this algorithm, the technique that generalizes the fuzziness index is selected, adding an α parameter that allows, according to its value, to adopt different behaviors between the fuzzy c-means and the fuzzy c-means with enhanced fuzziness partitions (Zhu *et al.* 2009). Likewise, the option that modifies the fuzzy *c*-means algorithm has been considered, improving fuzziness partitions through a modification in the objective function (Höppner and Klawonn 2003).

Therefore, this paper proposes an extended version of the c-means generalized fuzzy clustering algorithm with enhanced fuzzy partitions. Therefore, a new reward term is considered for membership to a single point of the sample x_j in order to force sharper assignments (see Zhu *et al.* (2009) for more details). Taking these penalties into account, the objective function is as follows

$$J_{GIFP-FCM} = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{2} d^{2}(x_{j,}v_i) - \sum_{j=1}^{n} a_j \sum_{i=1}^{c} u_{ij}\left(1-u_{ij}^{m-1}\right) \quad (1)$$

$$a_j = \alpha \, min\left\{d^2\left(x_j, v_s\right) \mid s \in \{1,\dots,c\}\right\} \quad (2)$$

In this way, the λ parameter that is used by the generalized fuzzy clustering algorithm c-means is replaced by the parameter α for the reward of memberships.

Based on the objective Eq. (1) and the restrictions imposed by the parameter α in Eq. (2), the membership of each data to each cluster *i*, as well as to the cluster center *i*, are given in the GIFP-FCM algorithm by the following equations.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d^2(x_j,v_i)-\alpha min_{1\le s\le c}\left(d^2(x_j,v_s)\right)}{d^2(x_j,v_k)-\alpha min_{1\le s\le c}\left(d^2(x_j,v_s)\right)}\right)^{\frac{1}{m-1}}} \quad (3)$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \quad (4)$$

where *m* is the fuzziness index, *n* is the total number of data, *c* is the number of clusters, x_j is the j^{th} data or sample, u^{ij} is the membership of data *j* to cluster *i*, v_i is the center of the cluster *I* and *d* indicate the mathematical distance used.

In summary, the execution of the clustering algorithm GIFP-FCM is described in Fig. 5.

Step 1 The number of clusters $c(2 < c < n)$, the treshold ϵ, the fuzzisness index m and the number of iterations T are stablishing. The fuzziness partition $u_{ij}^{(1)}$ and the index of each iteration $l = 1$ are initialized.
Step 2 The centers of the partitions $v_i^{(l+1)}$ are calculated and using (4).
Step 3 The membership functions $u_{ij}^{(l+1)}$ are calculated and using (3).
Step 4 If $\|u_{ij}^{l+1} - u_{ij}^{(l)}\| < \epsilon$ or the number of iterations $l > T$, then the algorithm is finished by returning the result of the clustering (cluster centers and membership functions matrix). Otherwise $l = l + 1$ and return to Step 2.

Fig. 5 Pseudocode with the steps of the GIFP-FCM algorithm

Although this technique offers very good results in classification, the potential offered by this new clustering algorithm for modeling systems through a neuro-fuzzy system has not been yet fully exploited. For this reason, it has been decided to incorporate this clustering algorithm into a Mamdani neuro-fuzzy structure (Gajate *et al*. 2010). These types of systems use fuzzy membership functions to determine both the background and the consequences of the "if-then" rules. The application of a fuzzy clustering algorithm in the inference system serve to initially set fuzzy rules. In this work, it is assumed a fairly extended design condition, which consists in choosing the number of rules equal to the number of clusters obtained. One of the advantages of this type of system is that if the membership functions are derivable and supervised learning algorithms can be used for setting parameters (Beruvides *et al*. 2015). For that reason, the error backpropagation error is applied in this study.

4.2 Model training

The next step within the proposed method is the adjustment of the parameters of the two modelling strategies. For this, a dataset composed of 70 samples for training and 21 for validation was used. Specifically, the structure of the dataset has as output the average absolute surface roughness (*Ra*), expressed in nanometers (nm), and as inputs the quadratic value of the feed per tooth $(f_z)^2$ normalized in relation to the radius of the tool (*r*), both expressed in nanometers (nm), and the mean quadratic vibration on the Z axis ($A_{c,rms}$) normalized in relation to its maximum value (A_{max}).

For the first modelling strategy, the values of the HIM model parameters obtained in the optimal adjustment, using simulated annealing algorithm, were: A first order polynomial (m = 1), a neighbor k = 1 and a fuzziness coefficient p = 1.27. A more detailed description of the optimal adjustment of the parameters can be found in Castaño *et al*. (2015b).

In contrast, for the second model proposal, the values of the GFCM model parameters obtained in the adjustment by trial and error during a number of iterations IT = 400, using the supervised learning backpropagation error algorithm, were: a number of clusters c = 6, a threshold ε_1 = 1, fuzziness index p = 1.2, parameter α = 0.9, number iterations IT = 1000, a learning rate of 0.056 and a threshold $\varepsilon_2 = 10^{-4}$.

From the results can be remarked that although both models fairly accurately predict surface roughness, it is interesting to note that the absolute mean error is 9% for GFCM and therefore, much higher than that obtained with HIM (0.2%).

Table 4 shows some previous AI-based models developed for quality control in some industrial processes and its performance results in comparative way. The comparison highlights the industrial process, the monitored or controlled variable, the AI-based modeling strategy and the prediction error obtained by each model. In addition, the computed error shown in this table corroborates the wide range of values most of them accepted in industrial setups and paves the way to determine which modeling technique between HIM and GFCM in estimating surface roughness is better according to the nowadays state-of-the-art.

4.3 Model validation

In addition, the two models were validated with 22 experimental tests with other operating conditions and their performance was evaluated using the following figures of

Table 4 Comparative study of different quality control AI-based models indicating variable, model and error

Industrial process	Components manufacturing of metal alloys									Components manufacturing with additive substrates
	Sensor manufacturing (Castaño *et al*. 2019)			Milling (Meso scale) (Beruvides *et al*. 2017)			Milling (Micro scale) (Villalonga *et al*. 2020)		Micro-drilling (Ranjan *et al*. 2020)	Dry CNC turning (Marani Barzani *et al*. 2015)
Variable to be controlled	Data reliability			Surface quality					Hole roundness	Surface roughness
AI-based modelling strategy	MLP	k-NN	SVM	ANN	BN	HIM + SA	MLP	HIM + SVM	ANFIS	FL
Error in prediction (%)	18.7	11.4	4.42	10.41	13.05	2.68	40	33	8-10	5.4

*Multi-layer perceptron (MLP), k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Artificial Neural Network (ANN), Bayesian Networks (BN), Hybrid Incremental Modelling (HIM), Simulated Annealing (SA), Adaptive Neuro Fuzzy Inference System (ANFIS) and Fuzzy Logic (FL)

Table 5 Comparison between the merit figures of both model proposals

Performance indices	HIM	GFCM
SSE	52912.44	193454.35
NSSE	16.60	31.74
FPE in %	16.95	35.97
ENV	33.55	67.72
MRE in %	16.71	15.08

merit (Table 5): Sum Square Error (SSE), Noise in the Sum of Square Errors (NSSE), Error of Final Prediction (FPE), Estimated Noise Variance (ENV) and Mean Relative Error (MRE).

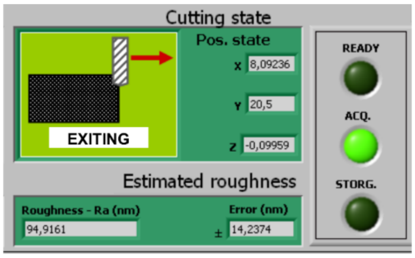
In Table 5, it can demonstrate that both models quite accurately predict surface roughness using the same 22 samples for both kind of models. Therefore, it is difficult to make a decision on which of both model proposals should be embedded in the software platform. The ultimate goal is to verify the real-time execution of the roughness estimation, GFCM is initially chosen. Subsequently it is shown that this model has very good performance, in terms of ease of implementation and integration.

5. Results of estimation of surface roughness. Viability of integration

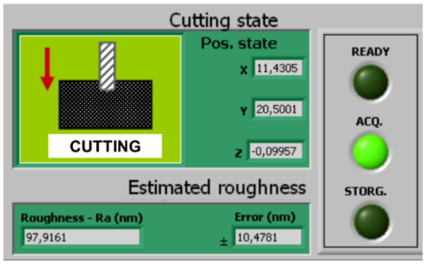
In this section the main issue is to assess real-time behavior of the subsystem that estimates surface roughness and that has been described previously in section 4.1 (model training) and in subsection 3.1.2 (method for prediction of surface roughness). As it was previously mentioned, the proper behavior of the system in real-time is very important and for this, an evaluation of the feasibility of integrating a method dedicated to online roughness estimation must be done, in parallel to the execution of other methods, such as the cutting state detection (see subsection 3.1.1).

Of all the adjustments and evaluations performed, the validation of the system is conducted in the same 22 different situations not known beforehand by the system is chosen, during the generation of roughness models in the training phases. The way to present the monitoring system the estimated roughness is depicted in two different pictures. Firstly, the result of the online estimation can be presented while the micro-milling operation itself is carried out, simply by observing the user interface of the program at runtime. Fig. 6 shows a screenshot of the graphical user interface of the developed system. The images correspond to a slot with a tool of 1800 μm in diameter, at a rotation speed of 15000 rev/min, 138 mm/min feed and an axial depth of 200 μm. In this regard, Fig. 6 illustrates the visual output of the process state and the current surface roughness value in two different operating conditions: (a) when the insertion of the tool into the workpiece is partial and (b) when the insertion of the tool into the workpiece is total.

Secondly, the result of the roughness estimation by the system can be stored in the warehouse of the system in order to generate a knowledge database. The first variable

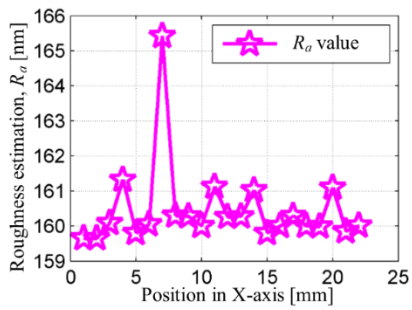


(a) Partial insertion of the tool into the workpiece

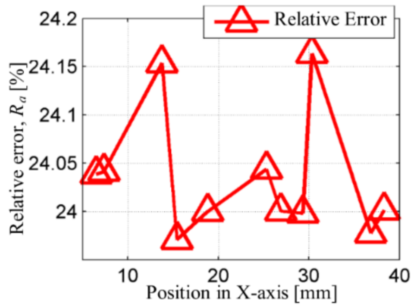


(b) Total insertion of the tool into the workpiece

Fig. 6 Display interface of the quality monitoring framework in a micro-milling operation



(a) Value of *Ra* estimated for the entire operation



(b) Its corresponding relative error obtained in the estimation

Fig. 7 Results of the estimation of the surface roughness during a micro-milling operation

storage is time, measured in milliseconds. The following are the inputs to the model that are the vibration, consisting of the normalized RMS value according to the maximum absolute value of the filtered signal in the considered interval, and the advance per square tooth divided by the radius of the tool. All in nanometers. The fourth is the output of the model, the estimated roughness, while the fifth is the error of that estimation.

From the analysis of the 22 samples, an average surface roughness value of 160.48 nm is estimated with an error in the estimate of 24.07%. Fig. 7(a) shows the result of the

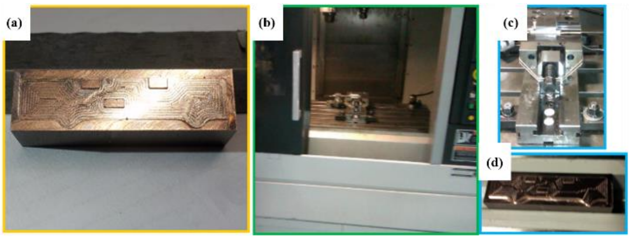
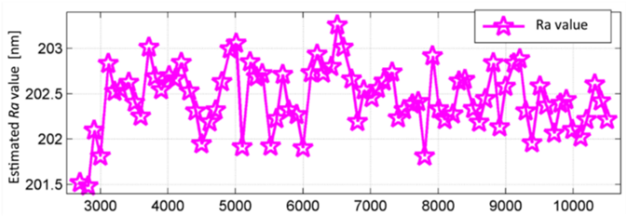
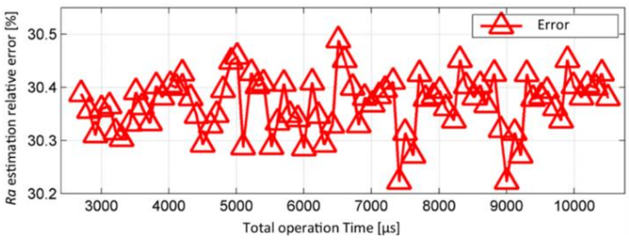


Fig. 8 (a) aerospace component manufactured; (b) assembly; (c) vibration sensor; and (d) workpiece mounted



(a) Value of *R*a estimated for the entire operation



(b) Relative error obtained in the estimation

Fig. 9 Estimation of surface roughness during a micro-milling operation

sample corresponding to a micro-milling operation. On the other hand, Fig. 7(b) shows the error of that estimation. Therefore, it can be determined that the real-time, modular, network and reconfigurable system is capable of estimating surface roughness online, in parallel to the execution of other real-time modules, such as the cutting state detection.

6. Industrial application of the framework. Real-world evaluation

The final step is to applied the developed framework for intelligent monitoring to industrial manufacturing process. The real-time evaluation of the supervision strategies in real-time was carried out by manufacturing a complex part corresponding to a critical aerospace component. The material of this piece, as in all the tests carried out in this work, is a tungsten-copper alloy (W22Cu78).

The experimental platform was deployed in the headquarters of a real company. Fig. 8(b) shows the assembly of the monitoring framework in a Mori SEIKI Dura Vertical 5060 machining center with an MSX-504 III CNC model.

The manufacturing process of this piece includes the performance of different micro-milling operations (slotting, planning, contouring, among others) in a continuous way. Fig. 8(a) illustrates the final finish of the work piece from the micromachining process. At first glance, it can see the complexity of the operations that were performed to obtain slot, contour, islands, planned and cashier profiles, among others.

Initially, the configuration and adjustment of the parameters of the framework for intelligent quality monitoring is performed for the new machine and the specific process to which the intelligent supervision strategy is going to be applied. Once all parameters are set, the correct operation of the sensors and the entire system was checked.

The results of the estimated surface roughness show that the monitoring framework is able to estimate on-line the *Ra* with very satisfactory results. Fig. 9(a) shows the result corresponding to a micro-milling operation, where a prediction in the *Ra* average value of 202.44 nm can be observed, during the whole manufacturing process of the piece. In contrast, the error of this estimation is shown in Fig. 9(b). An average error in the *Ra* prediction of 30.72% is observed. This error is relatively high for academic and theoretical studies but rather than realist and appropriate for industrial applications with high uncertainty, noise and very limited real-time sensor data is available (i.e., one non-intrusive and low cost sensor for measuring the vibration in the Z axis). On the contrary, the feed per tooth remains constant at 300 mm/min. throughout the experimental study.

7. Conclusions

This paper presents a real-time, distributed, modular and networked framework for intelligent quality monitoring is designed and implemented. In addition, different computational methods were embedded for a parallel real-time running such as a cutting detection procedure, interruptions calculations, and on-line surface roughness estimation in a microfabrication process. For this purpose, two computational intelligence-based modeling strategies for on-line estimating the surface roughness in micromachining processes are considered and reported in this paper. These two methods are HIM and GFCM.

The embedded model-driven approach for a quality monitoring framework is evaluated at laboratory and industrial scale in micro manufacturing processes. All the embedded strategies developed are rigorously assessed in real-time, through simultaneous and parallel execution of all modules that compose the final system setup. In order to accomplish the evaluation, tests carried out in micromachining operations. Different figures of merit that consider the accuracy for estimating surface roughness and appropriate cutting state in micromachining operations are analyzed. The suitability and effectiveness of the framework for coping with the intrinsic complexity of micro-scale manufacturing processes is demonstrated, thus leading to a substantial improvement in their operation and efficiency. Finally, work will continue to refine and explore deep learning methods in cloud-based distributed monitoring systems.

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