Development of an Innovative Tool Wear Monitoring System for Zero-Defect Manufacturing

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***Abstract*— High speed machining (HSM) is a technology employed in various industries and is characterised by high flexibility regarding geometrical forms, high productivity as well, as improved workpiece surface quality. In order to exploit the full potential of HSM, the most significant challenges which must be overcome are the frequent process disruptions and the high tool wear rates.**

This paper outlines a feasibility study of improving the efficiency in the utilisation of HSM by developing an innovative tool wear monitoring system interconnected with an intelligent adaptive control system. The tool wear monitoring system would achieve accuracy and reliability on an unseen level for the on-line quantification of tool wear by integrating indirect measurement methods, sophisticated wear models and intelligent computational methods.

The adaptive control system connected with the machine tool will use the tool wear information in order to determine the most appropriate moment for tool change while balancing maximum workpiece quality and maximum tool life. The optimised use of tools will enable stable workpiece quality and significant cost savings. Through the real-time adaptation of cutting parameters, an optimised tool change can be achieved despite varying process parameters.

The proposed system will be portable and adaptable to diverse machine tool controls and machine tools, independent of the manufacturer. It will be applicable to various workpiece and tool types, with minimised learning effort required due to the use of intelligent descriptors to describe the wear influencing variables. The system would enable end-users to efficiently use HSM technology. Its benefit in the form of improved process capability and additional cost savings could be quite vital in future projects within the automotive mould and die industries.

***Index Terms*—Tool condition monitoring, high speed metal cutting, adaptive control system, artificial neural networks**

I. Introduction

A. Technical Quality

Worldwide, manufacturing industry is undergoing significant changes. The globalisation of the industry as well as constantly decreasing product life-cycles and increasing product customisation has put enormous pressure on European manufacturing industry in recent years. European manufacturers must acquire a competitive advantage in production technology in order to withstand these pressures, in particular the pricing pressure of Asian competitors. This, and the never ending financial uncertainties has motivated the 'ManuFuture' platform to establish the Factories of the Future Research Association which supports the public-private partnership on future manufacturing technologies, and aims to develop innovative technologies which enable a competitive and sustainable manufacturing in Europe. Typical work programmes have included topics such as "Towards zero-defect manufacturing", encompassing the development of technologies which enhance the capability of manufacturing processes and thus represent a step towards zero-defect manufacturing.

A major factor which significantly reduces the capability of machining processes is tool wear, as it influences the cutting edge geometry thereby determining the quality of the produced part. The tool wear and hence the tool life is influenced by several factors originating from the workpiece, the workpiece material, the cutting parameter, the machine tool and the cutting tool itself. Some of these influences are subject to fluctuations which can be very difficult to control (e.g. material inhomogeneity). Therefore, in large-batch production, considerable fluctuations in tool life can be observed although the controllable machining conditions remain unchanged for each part. In contrast to this, the machining conditions have to be adapted to each specific machining task in single-item production. In this case, an accurate prediction of tool life is even more difficult as there is limited knowledge of the effect of the new cutting conditions on tool wear.

If a cutting tool is used beyond a certain tool life specification, the workpiece quality will deteriorate. Tool wear may then lead to:

- Reduction of geometrical and dimensional accuracy due to cutting edge displacement as well as tool and workpiece displacement as a result of increased process forces,
- Deterioration of surface quality through impaired cutting edge geometry,

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- Formation of undesired residual stresses in the workpiece surface layer through increased mechanical and thermal loads.
- Alteration of surface layer structure through increased process temperatures.

In either case additional reworks, customer complaint or scrap occur. Due to these problems, the tool life fluctuations are statistically analysed and a very early pre-set time for tool change is chosen. Hence, the full application potential of most of the tools is not utilised. Instead, the additional consumption of tools and the loss of time due to frequent tool changes lead to high production costs. A recent review of on-line tool condition monitoring is presented in Ref [1].

The problems related to tool wear basically apply to all machining processes. However, these problems are present to a high degree in High Speed Machining (HSM) processes, which can be defined as machining with significantly higher cutting speeds and/or feed speeds compared to conventional machining. HSM is characterised by a high flexibility toward geometrical forms, high productivity, as well as likely to improve surface quality and geometrical accuracy. The potential and advantages HSM processes is significantly higher than currently being exploited by the manufacturing industry. For example, it was estimated by Ref.[2] that productivity increases of up to 500 % could be achieved if the full potential of HSM were utilised. The most significant challenges which must be overcome in order to exploit the full potential of HSM are the reduced process reliability and capability, due to high tool wear rates. These occur due to the extremely high loads placed on the tool during the HSM process, which result in increased process temperature and demanding process dynamics compared to conventional machining [3].

HSM is widely defined as machining with significantly higher cutting speeds and/or feed speeds compared to conventional machining. Increased cutting speed can be utilised to increase the material removal rate at a constant under formed chip cross-section and thereby reducing cycle time. If the increased cutting speed is utilised to decrease the un-deformed chip thickness at a slightly increased material removal rate, the workpiece surface quality can be improved and consequently manual rework avoided [4]. Moreover, an improved surface quality can often be observed through the change of the chip formation mechanism at higher cutting speeds.

Hence, tool wear must be monitored and controlled in order to “approach” the goal of zero-defect manufacturing and simultaneously exploit the full potential of HSM. However, statistical monitoring methods reach their limits, particularly if single-item production processes are to be controlled. Therefore, on-line tool wear monitoring by intelligent and reliable sensor systems combined with an on-line process control become a necessity. This is in line with the ManuFuture proactive initiative which stipulates the development of condition monitoring systems as a primary research objective [5]. It thereby maintains the manufacturing process at maximum performance despite the many influences of the machine, the workpiece, the process and the tool itself. A monitoring reliability of more than 95 % is targeted in order to comply with sophisticated industrial requirements. Existing tool wear and tool condition monitoring systems are not capable of determining tool wear with this reliability in an industrial environment and therefore do not represent a solution for HSM process monitoring and zero-defect manufacturing [6].

The need for such a technology has been demonstrated by factory suppliers and end-users in the automotive, aerospace, electrical and optical industries, with various technological roadmaps and market studies evaluating the implementation of adaptive and intelligent production processes as a top priority. The development of high performance applications was found to be a further priority for these industries. Ref. [7] reported that 86.4 % of surveyed enterprises intended to establish adaptive, intelligent and/or high performance processes in their production. It is therefore clear that there is a demand for this technology and that such a technology will enable the European manufacturing industry to secure its global position in the manufacturing market.

B. Objectives

This paper outlines a feasibility study on the development of an innovative on-line tool wear monitoring system and a controller which is capable of adapting the HSM process in real-time, taking the current state of tool wear into consideration. This innovative System called Monitoring and Adaptive Control System (MACS) is envisaged to be developed for high-speed finish milling processes which present the most demanding challenges and exhibit the most significant benefit. The tool wear information shall be used for:

a) Precise determination of the most appropriate moment for tool change, balancing maximum tool life and maximum workpiece quality, thus enabling stable workpiece quality with best possible use of tools,

b) Control of cutting parameters in order to assure the implementation of a tool change at the most appropriate moment,

c) Real-time adaptation of the tool trajectory for the compensation of the cutting edge displacement due to tool wear.

The MACS will thereby significantly improve the process capability and productivity at end-user sites through:

- Improvement of dimensional and contouring accuracy,
- Improvement of workpiece surface integrity,
- Decrease of production time,
- Decrease of machine tool downtime,
- Decrease of tooling costs,
- Avoidance of rework and scrapped workpiece,
- Avoidance of tool breakage.

The scope of the envisage system as well as a summary of its technical content is listed in Table 1.

TABLE I. SCOPE OF MACS

Manufacturing scope or requirement	Content of system
Improvement of time invariant monitoring solutions by: - Real-time control of process parameters, - Use of pre-processing prognosis, - Use of proactive controls, - integrated in production line/cell	- Development of a system for real-time monitoring of tool wear and adaptive control of high-speed milling processes - Real-time adaptation of cutting parameters and tool trajectory - Prognosis of tool wear progress prior to execution of critical machining cycles - Integration of system into machine tool and control
Application of sensors for process diagnostics, monitoring and visualisation	- Indirect on-line tool wear and direct off-line quality measurement through multiple sensors - Visualisation of monitoring results and adaptive control through system
Integration of cognitive systems will enable the development of intelligent and self-optimising machines for “zero-defect” manufacturing with increased process capability	- Intelligent, self-learning computational methods for correlation of sensor signals and tool wear could generate unseen levels of accuracy and reliability - Application of MACS will lead to increased process capability
System approaches for monitoring and data processing of dimensional fluctuations	- On-line monitoring of tool wear for adaptive control of cutting process and thus reducing dimensional fluctuations of workpiece - Off-line measurement of dimensional fluctuations to train the self-learning system
Efficient simulation tools/methods to predict machining system behaviour for operation planning and in-process monitoring	System predicts tool wear evolution for the next machining cycle in order to implement an appropriate tool change strategy
Intelligent manufacturing systems in support of customising and build-to-order strategies	System is particularly designed for high accuracy and reliability under changing machining conditions and therefore fulfils the requirements of single-item and small-batch production of customised products
Extensive integration capabilities in production equipment of intelligent, autonomous, self-adaptive devises at low cost for process monitoring, control and quality management	- Facile integration of system sensor (for tool wear and quality measurement) and adaptive control system into machine tool and control through standardised interfaces - Correlation of sensor signals with tool wear is enhanced by the inclusion of multiple parameters which describe the influence of machine tool, cutting tool, workpiece, etc. on tool wear and thus, the tool wear monitoring system can be used in different machine tools and machining conditions with significantly reduced training effort - Considering the price-performance ratio of the MACS as a primary development guideline in order to guarantee large industrial exploitation

II. CASE STUDY APPLICATIONS

HSM is widely used in aerospace, automotive, medical, mould and die industries. MACS envisages these application fields through active participation of industry end-users. As tool wear exerts significant influence on the workpiece quality, tool wear monitoring becomes highly important. The mould/die and automotive industry would gain the most from the MACS, hence these two sectors have been the focus during the evaluation phase of the MACS.

A. *HSM in Mould/die and System Concept*

The ManuFuture initiative identified the tooling industry as a key technology sector, since product innovations strongly dependent on innovations and developments on mould, dies and tools [8]. This sector manufactures moulds, dies and special tools for the production of almost all industrial products which find application in automotive, aircraft, electronics, household, equipment goods and micro-devices. Seven thousand European companies (95 % of them SMEs) with more than 100.000 employees achieve an average annual turnover of €13 billion in this sector [9]. Besides the pricing pressure, the tooling industry is faced with increasing demands for customisation, accuracy and delivery time. A high percentage of all moulds and dies are manufactured in single-item production. This fraction amounts to 99 % in companies that specialise in the production of large moulds and dies. This creates a demand for manufacturing technologies that enable a more reliable, flexible and faster manufacturing of high quality mould and dies.

The central theme of the development focuses on embedding MACS within the machine tool (Figure 1).

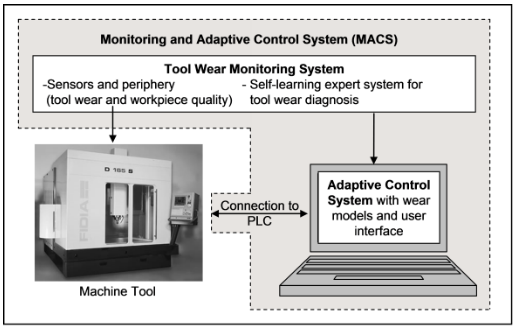

Figure 1. Concept of the Monitoring and Adaptive Control System.

1) *Tool wear montoring*

Due to the confined accessibility to the cutting edge during a milling operation, direct on-line measurement of tool wear is not possible in most cases. Since on-line measurement is essential for the real-time control of the cutting process, indirect on-line measurement of tool wear must be incorporated. Indirect on-line measurement requires the continuous monitoring of the cutting operation by sensors and the correlation of these signals with the tool wear by intelligent computational methods. Investigations in the field of on-line tool wear monitoring show that it is not sufficient to regard a single sensor signal if different manufacturing conditions are to be considered [5]. Hence, multiple sensor signals will be applied for the on-line measurement. Examples of measuring signals which can be measured and correlated with the tool wear are cutting force, torque, spindle drive current, vibration, acoustic emission, sound and temperature. Additional sensors for the off-line measurement of product quality in terms of dimensional accuracy and surface integrity will be applied to the machine tool in order to automatically create quality related data. This quality control data is required for the adaptation of the machining process.

2) *Sensor technology*

There are a large number of sensors currently available in the market. Their sensitivity to tool wear differs, depending on sensor type and on the manufacturing process. The effectiveness of different sensors, such as dynamometers, strain, vibration and acoustic emission sensors, microphones, thermocouples and infrared pyrometers will be evaluated after which, the most appropriate sensor technology for tool wear monitoring in high speed milling operations will be established. The application of tactile, optical and laser sensors is foreseen for the measurement of the product quality. The demand for high cost-efficiency of the system will be considered as a primary selection criteria of the sensor technology.

3) *Adaptive control system*

The adaptive control unit of the MACS uses the tool wear and workpiece quality data of the tool wear monitoring system in order to optimise the machining process.

4) *Interface between MACS and machine tool*

The interoperability between the MACS and different machine tools and machine controls is an important issue for the aspired broad exploitation of the system. The control unit and the user interface of the MACS are connected to an external card-based industrial computer which is connected to the programmable logic controller of the machine tool. This allows the bidirectional transmission of signals for the optimisation of the machining process. The advantages of such a system compared to a CNC integrated solution are the facile adaptability to different production systems, the high portability and the modular expandability of functionalities through the installation of additional plug-in cards.

B. Automatic Tool Wear Diagnosis

Approximately 2.3 million people are directly employed in the European automotive industry of which about 45 % can be apportioned to automotive suppliers. The turnover of the European automotive industry amounted to €550 billion in 2005 [9]. As of 2015 [10], the turnover generated by the automotive sector represents 6.5% of EU GDP while the industry has ripple effects throughout the economy, supporting a vast supply chain and generating an array of business services. According to the European Automobile Manufacturer's Association's facts, the following two points are clear:

Creating skilled jobs-

- 12.2 million people - or 5.6% of the EU workforce - are employed in the sector.
- The 2.3 million high-skilled jobs in automotive manufacturing represent 7.7% of the EU's manufacturing employment.

Manufacturing in Europe-

- Vehicle manufacturing is a strategic industry in the EU, where 18.4 million cars, vans, trucks and buses are manufactured per year.
- Automobile manufacturers operate some 296 vehicle assembly and production plants in 26 countries across Europe.

The automotive industry is not only a large customer for high speed machined moulds and dies but also applies the HSM technology for the manufacturing of engine components (engine block, cylinder head). Furthermore, innovative materials such as metal matrix composites and reinforced plastics find their way into automotive industry due to their excellent stiffness to weight ratio. These materials are difficult to machine with conventional cutting speeds. High speed machining offers advantages for these applications due to a change of the chip formation mechanisms at higher cutting speeds. HSM also allows the economical machining of hardened materials resulting in the substitution of other machining technologies, such as die-sinking electrical discharge machining and grinding, and bypassing the subsequent hardening to complete the manufacturing process.

Intelligent hybrid systems, such as fuzzy logic and neural networks have widely been tested in laboratory for the detection of tool wear based on a set of input parameters [11, 12]. However, the reported diagnosis approaches work in laboratory environments but not as industrial application due to the insufficient availability of input values in current approaches that is, the input values are not suited or comprehensive enough to describe the entire tool wear diagnosis problem. In practice, this means that the developed systems function reasonably well with the data recorded in the laboratory test but they do not function within an industrial environment [6, 13, 14]. In addition, the training and tuning of these systems in industrial sites would be extremely time consuming if all the possible tools, workpiece materials and corresponding cutting conditions (over a thousand possible combinations) were to be covered.

The innovation adopted in the MACS focuses on an approach that can be used in the industry in different or a wide number of machining environments. In order to achieve this goal, the "Advanced Intelligent Design of Complex Systems" method is applied (Figure 2), as this is most suited to solutions of general optimisation problems. The method specifies the transformation of so-called primitive descriptors into intelligent descriptors and creates a sophisticated database for automatic tool wear diagnosis. The transformation is steered by means of experts so that their knowledge is inherent in the intelligent descriptors. The intelligent descriptors will be extracted from sensor signals and extended for the first time by additional machine tool, cutting tool and workpiece material related descriptors in order to allow accurate tool wear monitoring in industrial applications. Intelligent descriptors are characterised by the fact that they include the basic wear determining information. This is achieved through features extracted from indirect tool wear monitoring sensor signals (such as vibration, acoustic emission, cutting force etc.), workpiece material parameters (e.g. tensile strength), dynamic response (excitation forces/stiffness) of the machine tool-workpiece-cutting tool system and lubrication. The database will be an elementary part of the self-learning intelligent hybrid diagnosis system.

The basic choice of monitoring signals together with the choice of signal analysis techniques plays a major role in the process of developing the intelligent descriptors. The chosen techniques have to be efficient and reliable in tool wear monitoring, with attention paid to the time the signal analysis takes since due to the progressive development of wear the time for diagnosis and prognosis of tool wear is limited. The intelligent descriptors must also allow the correct recognition of the rapid change in wear rate i.e. the dramatic increase of wear which can often be observed when the tool reaches its end of life. The identification of the intelligent descriptors as well as the development of simple, standardised tests for the quantification of particularly stiffness/dynamic response related values are important issues and require multi-disciplinary expert knowledge.

1) Self-Learning intelligent hybrid system for tool wear diagnosis.

The self-learning intelligent hybrid system of the MACS learns from a set of examples which connect the intelligent input descriptors with the tool wear (Figure 2). A number of intelligent classification methods come into consideration for this purpose. The main advantage of the intelligent descriptors is that reliable tool wear diagnosis is possible with significantly reduced training effort despite the influences emerging from the change of workpiece material and type of machine tool or cutting tool. The MACS thereby fulfils the practical requirements which are claimed when the system is applied in small series or even single-batch production with frequently changing machining conditions.

A number of the intelligent descriptors are continuously allocated with new values which are derived from the sensor signals during the monitored machining process. The current state of tool wear can then be determined by means of the established classification and subsequently be used for the adaptive process control.

2) Adaptive control system: capabilities of the MACS

The adaptive control unit of the MACS is connected to the machine control and uses the tool wear data and workpiece quality data in order to:

- Determine the most appropriate moment for tool change, balancing maximum tool life and maximum workpiece quality,
- Adapt the cutting parameters in order to assure an optimised tool change, i.e. to shift the point of tool change if the interruption of the machining process for tool change is not allowed at the predicted moment,
- Adaptively control the tool trajectory for the compensation of the cutting displacement due to tool wear.

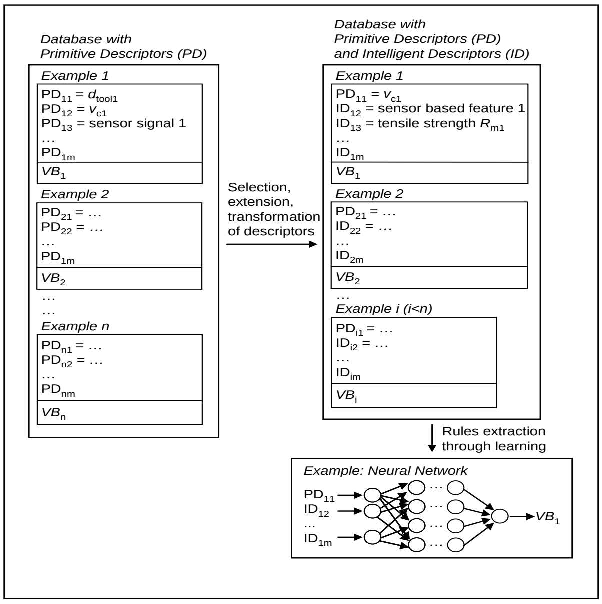

Figure 2. Tool wear diagnosis through "Advanced Intelligent Design of Complex Systems"

3) Determination of critical tool wear status and suitable tool change strategy

The most appropriate moment for tool change is characterised by the achievement of a critical state of tool wear at which the workpiece quality criteria can no longer be met unless a change of either the nominal machining parameters or the tool itself is made. This critical state of tool wear according to the wear criterion (Flank wear), V_{Bmax} must be determined prior to the machining process. The said value shall be determined from the analysis of both tool wear and achieved surface quality data recorded in preliminary machining operations by the tool wear monitoring systems.

Different tool change strategies must be applied according to the respective cases. On the one hand, the current tool wear state V_B can be continuously compared with the critical wear V_{Bmax} during the machining process. The MACS then sends the signal for tool change to the CNC as soon as V_{Bmax} is reached, in order to prevent the degradation of the workpiece quality. A relevant and commonly used case is that where tool change is not allowed (or recommended) before the completion of a machining cycle in order to avoid marking the workpiece surface through the tool change. However, the tool may reach a critical wear status during the course of the current operation. This means, that the time of tool change must be shifted through the adaptation of machining parameters (e.g. feed-rate, depth of cut, etc.). In order to implement such a tool change strategy, the progress of the tool wear over time must be predicted.

4) Dynamical mathematical modelling for tool wear prognosis

Prior to the execution of a machining operation, the current tool wear status is evaluated to include development of dynamic models featuring initial and in-situ prevailing tool wear status, machining operation, configurable machining parameters as inputs and resulting tool wear status and surface quality as outputs. Such a model allows the prediction of machining parameters thus guaranteeing the successful completion of the intended operation without surface quality degradation or tool breakage (V_{Bmax} is not exceeded).

In case the pre-process prognosis by the dynamical model shows that the machining configuration currently in use should lead to unsuccessful machining completion whereas another one will not, the latter configuration will be adopted for the following operation; otherwise, if there is no suitable machining parameter configuration, a tool change should be carried out immediately.

C. Modelling For Successful Tool Change and Machining Operation Completion

Two different system identification paradigms are considered as appropriate for the modelling of the high non-linearity associated with high-speed machining operations:

1. Non-symbolic modelling approach that relies on the application of data mining techniques. Data mining or knowledge discovery from data encompasses many different techniques, such as computer science, numerical analysis, and visualization that are used to extract implicit, previously unknown, and potentially useful information from data. To that purpose several statistical techniques predictive models such as artificial neural networks, decision trees, and nearest neighbour classification can be used.
2. Symbolic modelling approach that relies on the application of symbolic regression techniques. Symbolic regression or symbolic function identification employs regression techniques to analyse and model numeric

multivariate data sets. It identifies the input variables that set up significant changes on relevant output variables, whilst yielding a mathematical function and assessing its quality and generality. To that purpose symbolic regression relies on efficient evolutionary programming algorithms that perform stochastic iterative searches to estimate potential model expressions.

These two approaches have proven to be well suited to tackling industrial modelling problems where little information about the underlying system is available (and thus, no assumptions or preliminary model structure can be made) and involving handling large multivariate data set.

1) Dynamical Mathematical Modelling for Tool Wear Prognosis

Non-symbolic models refer to models that are not directly human-understandable. Instead of using human-understandable symbols, they use other knowledge formats such as weights, connections, etc. The best known data-driven model generation method based on non-symbolic modelling approach is artificial neural networks (ANN). ANNs are inspired by human brain cognitive ability where neurons (i.e. process units) are interconnected and grouped in layers. An input layer receives input data while an output layer provides output data. The main advantages of this approach are:

- Learning ability: Input-Output patterns are used to train the ANN. During the training (estimation) phase ANN error is iteratively reduced by using different algorithms such as the back-propagation method or genetic algorithms. From a mathematical point of view an ANN can be considered as a complex non-linear mathematical expression regressor. Furthermore, ANNs are universal approximators and consequently they can approximate any continuous function on a compact domain to any degree of accuracy.
- Generalisation: By means of a set of training data, the ANN is able to extrapolate or generalise its behaviour. This is a very interesting feature in order to reduce the data set cardinality as well as the number of experiments.
- Noise-Tolerance: The nature of the ANN computational process makes ANN less sensitive to input data noise than other data-driven model generators.

The main disadvantages of ANNs are:

- There are no precise rules to pre-determining ANN architecture (number of layers, neurons distribution, topology, etc.). A small neural network will provide limited learning capabilities, whereas a large one will overfit the training data, inducing generalisation loss.
- Heuristic-based approaches are used in order to define the most promising ANN architecture.
- ANN can be considered as a non-symbolic model (black-box) in which knowledge is not explicit. Many domain applications are not compatible with this fact.

2) Symbolic Regression

Many science areas are increasingly searching for models that fit specific data sets. The model in question is usually a mathematical expression with a set of coefficients (parameters) that have to be determined. In the best scenario, the model is known and the problem can be reduced to find this set of coefficients that fit data in an optimal way.

Curve fitting is considered a mathematical problem in which a curve fits a set of points. This process is carried out by applying mathematical methods such as least squares, or alternatively it can be reduced to a classical interpolation problem when the function has to perfectly fit the points.

If initial data have been experimentally obtained, an inevitable error in the measurement process has to be assumed. The way in which the impact produced by this error can be mitigated is by carrying out repetitive measurements so that a statistical analysis can be performed. Thus, there exist statistical techniques, like regression analysis, that provide the model parameters taking into account the error that can be present in data. Besides, other statistical techniques like lack-of-fit test provide an estimate of suitability of the evaluated model through a fitness value which considers measurement errors.

The technique that allows the searching of both the coefficients that best fit data and the model itself is known as symbolic regression. Symbolic regression is based on concepts known some decades ago, although the symbolic regression term is relatively recent [14, 15]. The first symbolic regression approaches were based on extensions of classical regression methods, and were called stepwise regression methods. In these methods, the targeted mathematical function is iteratively modified by adding and removing mathematical terms [16, 17]. Stepwise regression methods are supported by statistical concepts like regression analysis. So, initil data need to satisfy statistical requirements imposed by the statistical tests used to validate generated models. Other symbolic regression methods include data-driven heuristic model generation. This method is inspired by human cognitive process employing heuristic rules in order to drive the search process to find a mathematical expression that best fit data [18].

Both stepwise regression methods and data-driven heuristic approaches are only able to obtain limited models in terms of mathematical complexity. A priori information about the searched model is needed in order to state the more complex mathematical expressions search [19]. In addition to this, most of these methods require an exhaustive initial data set, coming from a factorial experiment design, where all the possible coupled variable modifications have to be considered.

Advances in information technologies have allowed the use of more sophisticated search techniques like evolutionary computation. By means of evolutionary computation the search problem, inherent in symbolic regression, can be faced avoiding the existing constraints in other approaches. Nowadays, evolutionary computation use has been a revolution in the symbolic regression domain. Its use has been extended to a great number of domains, from purely mathematical domain to engineering and industrial applications. With its help, symbolic regression can be considered as a very promising useful tool to assist scientists in the physical laws deduction process.

The main advantages of the evolutionary symbolic regression approach are:

- Free data format: no restrictions are imposed regarding the initial data format. On the contrary, in other statistical approaches repetitions are required or other statistical considerations: Gaussian error distribution, constant error deviations etc.

Free form model search: by using evolutionary computation and especially grammar-guided genetic programming, is possible to define the model searching space. Grammar definition supports the type of mathematical expression to take into account.

- Searching ability: evolutionary computation has demonstrated being the best technique when solving optimization and search problems in complex search spaces and in problems where no direct solving methods are available. Efficient search space exploration skills together with local extrema avoidance are two main virtues of this approach.
- Although this approach has an important computational cost, its performance improves that of most of other data-driven model generation methods.
- During the best model search process, besides the best-fit method other restrictions and objectives can be considered: penalize complex expression (parsimonious criterion), derivability conditions, etc.

Both, symbolic and non-symbolic modelling approaches are evaluated and the most suitable approach chosen.

3) Adaptive control of tool trajectory

Besides the implementation of a timely tool change, the tool wear information can also be used as an optimisation measure. As the tool wear causes a displacement of the cutting edge, the accuracy of the machined workpiece dimension and contour is reduced. A width of flank wear land of 0.2 mm will cause a deviation of approx. 0.035 mm if a cutting tool with a clearance angle of 10 ° and a rake angle of 0 ° is considered. Hence, the tool trajectory must be adapted by this amount in order to guarantee the requested geometry despite tool wear. If this amendment ought to be realised in real-time, comprehensive adaptations in the CNC have to be accomplished. The work must particularly focus on the look-ahead function of the CNC which processes and buffers the following 100 to 150 part program blocks in advance in order to maximise machining speed and smoothness. As it is not possible to access the already buffered data, they cannot be corrected with the current tool wear information. Moreover, there is no information about the duration of the buffered NC blocks. One way to overcome these difficulties is to apply the trajectory compensation to the NC code, empty the buffer and restart the look-ahead function. If the restart interval is small enough, a real-time adaptation of the tool trajectory will be possible. There is, however, still the need for a review of the Human-machine interface [20].

The participation of a CNC manufacturer is imperative due to the profound nature of the adaptations described. The work tasks for the development of the adaptive control of the tool trajectory would be exclusively led by a European HSM machine and CNC manufacturers.

4) Innovation beyond state-of-the-art

In order to achieve an unseen level of accuracy and reliabilities in excess of more than 95 % even under changing process conditions, parameters must be determined which account for the influence of external factors on the tool wear monitoring. For example, the stiffness of the workpiece clamping system and the machine tool, the cutting tool type and material, as well as the work material hardness and ductility significantly determine the tool wear behaviour and have not been explicitly considered in industrial TCMS’s. The development of such parameters represents an important progress beyond current monitoring systems. These as well as further features which will be extracted from sensor signals will be transformed into intelligent descriptors following the “Advanced Intelligent Design of Complex Systems” approach in MACS. Dependencies between the features and the tool wear, which can be described by theories and models, will be considered in this transformation. A universally valid description of the wear diagnosis problem is thereby necessary, so that an unrivalled diagnosis reliability and accuracy can be achieved. The real-time control of the machining process on the basis of the current state of wear becomes therewith possible for the first time. The MACS proposed focuses on the development of control algorithms which ensure the implementation of a tool change at the most appropriate moment in order to realise the desired workpiece quality at maximum tool usage.

III. Conclusion

This project contains several important new developments which overcome the current state-of-the-art. These are:

- A tool wear monitoring system with a new level of reliability and accuracy (more than 95 %) for industrial environment i.e. working at different machining conditions.
- An adaptive control system which compensates for cutting edge displacement due to tool wear and determines the most appropriate tool change strategy, using the tool wear monitoring system and:
- A tool wear prognosis model.
- A model for the determination of the critical state of tool wear.

IV. Further Work Suggestion

Multisensory systems development increases the total number of features which leads to an improved tool wear diagnosis accuracy. The lack of feature robustness at changing machining conditions is problematic, therefore in order to use an appropriate number of features, feature reduction methods need to be improved to include for example genetic algorithms.

A common drawback in the implementation of a HSM is that the machine configuration parameters (i.e. spindle speed, feed rate, depth of cut, etc.) are usually determined either through a relatively static database or based on the expertise of the operator. This fact usually leads to inefficient operation of CNC-driven systems and efforts needs to be focused here to accomplish automatic adjustment of operating parameters.

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