ELSEVIER
Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia CIRP 8 (2013) 421 – 425
www.elsevier.com/locate/procedia

14th CIRP Conference on Modeling of Machining Operations (CIRP CMMO)

# Monitoring and control of manufacturing processes: A review

P. Stavropoulos[a], D. Chantzis[a], C. Doukas[a], A. Papacharalampopoulos[a] & G.Chryssolouris[a]*

[a]Laboratory for Manufacturing Systems and Automation, University of Patras, Patras, 26500, Greece
* Corresponding author. Tel.: +30 2610 997262; fax: +30 2610 997744. *E-mail address*: xrisol@lms.mech.upatras.gr

**Abstract**

Online processing optimization through adaptive control can provide significant advances in process efficiency, tooling life and product quality. This paper describes conventional and enhanced methods for the monitoring and control of manufacturing processes. The differences between the available methods, architectures and the corresponding equipment are identified and evaluated. A systematic analysis of current and future systems and their components is made focusing on adaptive control systems implementation into manufacturing processes.


Selection and peer-review under responsibility of The International Scientific Committee of the "14th CIRP Conference on Modeling of Machining Operations" in the person of the Conference Chair Prof. Luca Settineri

*Keywords:* Adaptive; Control; Monitoring; Manufacturing processes

## 1. Introduction

There is [1] a variety of reasons for the installation of a monitoring system in a manufacturing process. Modern manufacturing equipment has to be flexible, sustainable and operative with minimum human interface, while machine tools have to operate free of errors. Two major problems in the field of metal cutting are tool wear and tool breakage, causing frequent downtimes. Tool breakage is a major cause of unscheduled stoppage in a machining environment, and is costly not only in terms of time lost, but also in terms of capital destroyed [1]. Previous studies state that the amount of downtime due to cutter breakage on an average machine tool is on the order of 6.8% [2], while others put the figure closer to 20% [3]. Manufacturing trends imply the need for higher machining speed, lower tool wear and reduction in the use of machining fluids in order for an increase to be achieved in productivity leading to a way of producing "more with less" [4]. Moreover, environmental footprint of the products is a key factor in today's manufacturing. The increasing price of energy and the current trend of sustainability have exerted new pressure on manufacturing enterprises that have to reduce energy consumption for both cost saving and environmental friendliness. Monitoring and control of manufacturing processes is becoming nowadays a driver for development and sustainability of manufacturing industries. Process monitoring is the manipulation of sensor measurements (e.g., force, vision, temperature) in determining the state of the processes. A machine tool operator performs routine monitoring tasks; for example, visually detects missing and broken tools as well as chatter from the characteristic sound it generates. Unmanned monitoring algorithms utilize filtered sensor measurements which, along with operator inputs, determine the process state. The states of complex processes are monitored by a sophisticated signal processing of sensor measurements. Process control is the manipulation of process variables (e.g., feed, speed, depth-of-cut) to regulate the processes [5], [6]. Machine tool operators perform on-line and off-line process control by adjusting feeds and speeds to suppress chatter, initiating an emergency stop in response to a tool breakage event, rewriting a part program to increase the depth-of-cut in order to minimize burr formation and many more.

Adaptive Control (AC) has been introduced as a method of optimizing machining variables on-line, during the process. AC has been classified [7] into 3


Selection and peer-review under responsibility of The International Scientific Committee of the "14th CIRP Conference on Modeling of Machining Operations" in the person of the Conference Chair Prof. Luca Settineri
doi:10.1016/j.procir.2013.06.127

main categories:

- **ACC** Adaptive Control with Constraints
- **ACO** Adaptive Control with Optimization
- **GAC** Geometry Adaptive Control

Typically, the **ACC** systems are utilized in roughing operations, where the material removal rate is maximized through the maintenance of the cutting forces at the highest possible rate, so as for the tool not to be in danger of breaking down.

In the **ACO** systems, machine settings are selected for the optimization of a performance index, such as production time, unit cost etc. Typically, the **ACO** systems have dealt with adjusting cutting variables for the maximisation of the rate of material removal, subject to parameter constraints, such as surface roughness, power consumption, cutting forces, machining time, cost and even more.

In the **GAC** systems, the economic process optimization problem is dominated by the need for product quality, namely dimensional accuracy and/or surface finish to be maintained. Such systems are typically used in finishing operations with the objective of a specific part quality being maintained, despite structural deflections and tool wear.

The purpose of the current study is to review the research done on Monitoring and control of manufacturing processes, to examine the impact of such systems on industry applications and discuss the current research directions.

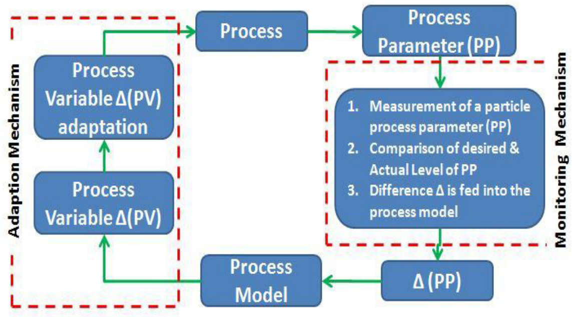


Fig. 1: Process – Monitor – Control Loop

## 2. Sensors and sensing devices

The techniques for the monitoring of machining have been traditionally categorized into two methods:

- Direct
- Indirect

The direct monitoring methods can achieve a high degree of accuracy, but due to numerous practical limitations, they are characterized as laboratory oriented techniques. One the other hand, the indirect monitoring methods are less accurate but more suitable for practical applications, at machine shop level. Auxiliary quantities are measured and empirically correlated with machining phenomena.

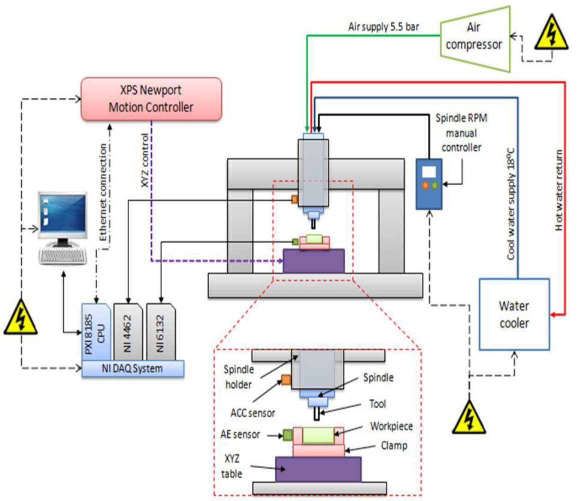


Fig. 2: Typical Multi-sensorial Monitoring System Schematic

Direct methods require vision systems utilization; however, illumination, cutting fluid and more, may interfere with the monitoring system and the machine tool, leading to an unstable system for production environments. Nevertheless, some measurement systems have been developed for the evaluation of th tool wear with the use of laser sensors that measure displacement and light intensity [8]. These methods are promising as they can measure flank tool wear greater than 40 μm. Moreover, the combination of CCD cameras can be used simultaneously for the acquisition of the tool images during machining [9]. Based on image acquisition and the creation of an image database, containing tools stressed under extreme conditions, an algorithm for further data processing can be created.

Due to the stability issues of the direct measurement methods, other systems, using signals such as force, torque, acoustic emission, acceleration have been developed. An important factor of a monitoring system's design is the phenomenon, which data will be acquired from, and the decision of the signal characteristic to be correlated with the phenomenon. Not all the types of sensors are capable of measuring the same phenomenon, with the same accuracy. Load cells are often attached to the machine structure for the measurement of cutting forces. Expensive dynamometers are often used in laboratory settings for precise measurements; however, they are impractical for industrial applications. In [10], [11] forces in milling operations were predicted from the current of the feed axis drive. Torque [12] is typically monitored on the spindle unit(s) with strain gauge devices. In addition, expensive dynamometers may be used, but are cost prohibitive in industrial applications. Power from the spindle and axis motors is typically monitored via Hall Effect and inductive sensors. These sensors may be located in the electrical cabinet, rendering them easy to be installed and guarded in the process. Due to the large masses of the used motors drives, the signal has typically a small bandwidth.

Numerous studies trying to correlate Acoustic Emissions (AE) with tool condition have been conducted [13]-[15]. For instance, in [13], the AE sensors are utilized for the acquisition of signals and specifically, the ring-down counts, rise time, event duration, frequency and event rate, correlating them with the chip status and consequently, with the tool condition. Using the RMS voltage of an AE signal during milling [15], the normal tool characteristics from the abnormal ones are distinguished. However, the AE sensors face some problems, regarding the radio-wave and electromagnetic noise. In [14], an intrinsic optical fiber for the monitoring of acoustic emissions has been developed in order for these problems to be overcome.

## 3. Modelling Systems

A number of schemes, techniques and paradigms have been used for the development of functional decision making systems that would derive a conclusion on machining process conditions, based on sensor signals [16]-[18],[2]. The cognitive paradigms most frequently employed for the purpose of monitoring in machining, are the Neural Networks (NN) and Fuzzy Logic (FL).

### 3.1 Fuzzy Logic

A fuzzy set is one without crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. A fuzzy set defines a mapping between elements in the input space and values in the interval {0, 1}. A membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1. The membership function can be any arbitrary curve, whose shape can be defined as a function suitable from the point of view of simplicity, convenience, speed and efficiency.


Fig. 3: Fuzzy Logic Data Processing

The FL decision making system has been used in quasi orthogonal cutting of metal alloys with sensor fusion of frequency features, extracted from AE signals, through diverse forms of signal analysis [19][19]. These features were processed by a fuzzy logic based pattern recognition method to develop a multi-purpose intelligent sensor system for classification of tool wear. The results can be considered positive and the FL decision making system as being capable of taking many factors into account.

### 3.2 Neural Networks

Numerous studies [21, 22, 23] , have been conducted in manufacturing, using neural networks specifically, in machining operations. In [24], the probabilistic NN (PNN) have been used for automated classification of the broaching tool condition by utilizing cutting force data.

Moreover, when combining data with more than one sensors for monitoring, the information should be synthesized with the appropriate method in order for the state variables to be determined. In [25], both NN and statistical criteria approaches have been used and evaluated to combine data derived from multiple sensors. Additionally [26],in order for a possible failure of the tool to be predicted, experiments have been conducted with different tools, such as fresh, worn, with chipped teeth or even broken ones. NN used as input data from multiple sensors and a multi-sensor chatter detection system for milling using two accelerometers and one axial force sensor, embedded in the milling machine, have been developed and tested. Good levels of NN accuracy were obtained from all the single sensor signals.

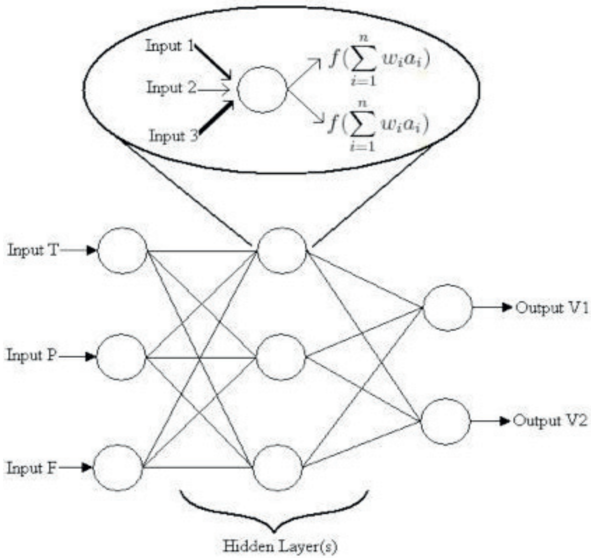


Fig. 4: Neural Network Schematic

## 4. Control Strategy

Many AC systems have been developed for different purposes and in different processes from milling [27]-[31] to robot machining [1].As observed in [27], the forces vary in 5-axis machining, specifically in impeller machining, due to the change of tool orientation, the depth of cut and the deep immersions, resulting in very high machining forces. Therefore, an AC system, in which are given as input, a reference force, the upper limit, and the real-time force measurement, has been developed. Then, the controller can override the feed-rate in order for the forces to be kept constant. The quality of sensors affects the system's performance. Similarly, the adjustment of the feed-rate for constant cutting forces has been investigated into [28]. This approach includes both off-line and on-line optimization.

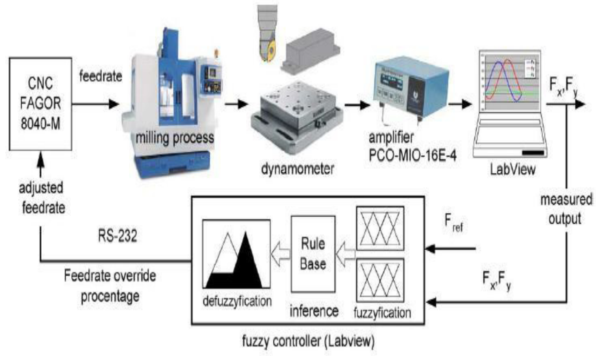


Fig. 5: Adaptive Control System [28]

The cutting variables were initially determined off-line, using an adaptive neuro-fuzzy inference system and a further optimization was conducted via the Particle Swarm Optimization method. During the process, the cutting forces were measured and used as input to a NN that over-rode the feed-rate by keeping the cutting forces constant. The results indicate that the material removal rate can be improved by 27%.

However, the use of dedicated equipment (sensors etc) for process monitoring increases the cost of an AC system. The spindle motor current has been utilized in [29], for the developments of a fuzzy control system, aiming at the on-line adjustment of the feed rate. A sensor-less AC system [30] having as an input to the controller, the cutting forces of x,y,z axes (measured indirectly from the current drawn by each feed-drive servo motors) has been tested, resulting in a greatly potential solution, due to the absence of additional monitoring equipment. Considerable work needs to be done towards the development of parametric algorithms, which will accept as input, machine tool variables and be adjusted to each case accordingly. Optimal control of the machining process not only does it increase productivity but also ensures safety during operation. In [31], a force control system technology has been developed. This includes two modes of operation; the "air-cutting mode" and the "force cutting mode". In the air cutting mode, the tool feed is scheduled through the prediction of the air and cutting zones of a CAD/CAM system. As a result, the productivity increases. In the force control mode, the controller monitors the cutting force, the cutting temperature and controls the feed over-ride, according to the difference between the real and the desired cutting force that ensures quality results. A self-tuning PI control, with anti-windup scheme for the force regulation in the robotic machining process, has been proposed in [1]. The dynamic and nonlinear process models, which have been used in the control algorithm design simulation, have been experimentally identified. The proposed self-tuning PI control is effective in force regulation during the machining process. The control performance and system stability are maintained during the process, although the cutting conditions are continuously changing.

## 4. Conclusion

Monitoring and control of manufacturing processes is becoming nowadays a driver for development and sustainability of manufacturing industries. The AC systems can increase the controllability and reliability of machining processes. AC has been introduced since 1960's but not yet has it matured enough to dominate the industrial environment. This paper summarizes some research results over the last years in monitoring systems for machining processes, decision making systems and AC systems. Nowadays, the need for quality, efficiency and sustainability in manufacturing is more important than ever before, due to the environmental impact, policies and regulations. Consequently, the need for implementing AC into production lines, for on-line optimization, not only under the scope of tool conditioning but also under the prism of making the manufacturing more efficient and more sustainable, is of great importance.

## 5. Future Trends

The future enhancement of machining systems and their operational performance will essentially depend upon the development and implementation of innovative AC systems. These novel systems will have to be robust, reconfigurable, reliable, intelligent and inexpensive in order to meet the demands of an advanced manufacturing technology.

The EC FP7 FoFdation project, which targets at the future enhancement of machining systems, is one of the currently running research projects. FoFdation envisions a 'Smart Factory' architecture and implementation that provides a promising potential of achieving significant benefits for the earlier visibility in manufacturing issues.

## Acknowledgements

The work reported in this paper was partially supported by CEC / FP7 NMP-ICT Programme, "The Foundation for the Smart Factory of the Future-FoFdation", (FP7-2010-NMP-ICT-FoF- 260137).

## References

[1] Chryssolouris, G., 2005, Manufacturing Systems: Theory and Practice, 2nd Edition 606p, Springer-Verlag, New York.

[2] Chryssolouris, G., Guillot, M., 1990, A Comparison of Statistical and AI Approaches to the Selection of Process Parameters in Intelligent Machining, Journal of Engineering for Industry, ASME, Volume 112, pp. 122-131

[3] Kurada S, Bradley C., 1997, A review of machine vision sensors for tool condition monitoring. Comput Ind 34:55–72

[4] Chryssolouris, G., Papakostas, N., Mavrikios, D., 2008. "A perspective on manufacturing strategy: Produce more with less", CIRP Journal of Manufacturing Science and Technology, Volume 1, No.1, pp. 45-52

[5] Chryssolouris, G., Patel, S., 1987, In Process Control for Quality Assurance, Industrial High Technology for Manufacturing, K. McKee, D. Tijunelis (eds.), Chapter 22, New York: Marcel Dekker, Inc, pp. 609-643

[6] G. Chryssolouris, M. Domroese, P. Beaulieu, "Sensor Synthesis for Control of Manufacturing Processes", Journal of Engineering for Industry, ASME, Volume 114, No. 2, pp. 158-174 (1992)

[7] Galip Ulsoy, A., Koren, Y., 1993, Control of Machining Process, Transaction of the ASME, Vol. 115.

[8] Ryabov, O., Mori, K., Kasashima, N., 1996, An In-Process Direct Monitoring Method for Milling Tool Failures Using a Laser Sensor, AIST, MITI, Tsukuba, Ibaraki, Japan

[9] Lanzetta, M., 2001, A new flexible high-resolution vision sensor for tool condition monitoring, Journal of Materials Processing Technology 119,pp 73-82.

[10] Lee B, Tarng YS, 1999 Application of the discrete wavelet transform to the monitoring of tool failure in end milling using the spindle motor current. Int J Adv Manuf Technol 15(4):238–243

[11] Du, R., Liu, Y., Xu, Y., 2001, Tool condition monitoring using transition fuzzy probability, 3rd International Conference on Metal Cutting and High Speed Machining, pp 375–393

[12] Koumboulis, F.N., Petropoulos, G.P., Mavridis, C.S., 2000, Fault detection in machining via torque estimation. IFAC Symposium on Manufacturing, Modeling, Management, and Control, Rio, Greece, pp 217–223

[13] Kakade, S., Vijayaraghavan, L., Krshnamurthy, R., 1994, In process tool wear and chip-form monitoring in face milling operation using acoustic emission, Journal of Materials Processing Technology, Vol. 44, Issues 3-4, pp. 207-214

[14] Inasaki, I., 1998., Application of acoustic emission sensor for monitoring machining processes, Ultrasonics, Vol. 36, Issues 1-5, pp. 273-281

[15] Srinivasa, P. P, Nagabhushana, T.N., Ramakrishna, R., PK, 2001 Tool wear estimation using resource allocation network. Int J Mach Tools Manuf 41:673–685

[16] Chryssolouris, G., Domroese, M., 1989, An Experimental Study of Strategies for Integrating Sensor Information in Machining" CIRP Annals, Volume 38, No.1, pp. 425-428

[17] Chryssolouris, G., Guillot, M., Domroese, M., 1988, A Decision Making Approach to Machining Control, Journal of Engineering for Industry, ASME, Volume 110, pp. 397-398

[18] Chryssolouris, G., Domroese, M., Zsoldos, L., 1990, A Decision-Making Strategy for Machining Control, CIRP Annals, Volume 39, No.1, pp. 501-504

[19] Klir, G.J., Folger, T.A., 1988, Fuzzy Sets Uncertainty and Information, Prentice Hall, Engelwood Cliffs.

[20] Teti, R., Manzoni A. 1998, Tool Wear State Identification by Fuzzy Logic Processing of Fused Sensor Data, 1st CIRP Int. Sem. On ICME, pp. 687-691

[21] Teti, R., Jemielniak, L., Donnell, G., Dornfield, D., 2010, Advanced Monitoring of Machining Operations, CIRP Annals – Manufacturing Technology 59, pp. 717-739

[22] Chryssolouris, G., Lee, M.,Pierce, J., Domroese, M., 1990, Use of Neural Networks for the Design of Manufacturing Systems, Manufacturing Review, Volume 3, No.3, pp. 187-194

[23] G. Chryssolouris, M. Lee, A. Ramsey, 1996, Confidence Internal Prediction for Neural Network Models, IEEE Trans-actions on Neural Networks, Volume 7, No.1, pp. 229-232.

[24] Axinte, D., 2006, Approach into the use of probabilistic neural networks for automated classification of tool malfunctions in broaching, International Journal of Machine Tools & Manufacture. 46 (12-13), 1445-1448.

[25] Chryssolouris, G. Domroese M., Beaulieu, P., 1992, Sensor synthesis for control of manufacturing processes. Transaction of the American Society of Manufacturing Engineers, pp. 157-174

[26] Kuljanic, E., Sortino, M., Totis, G., 2009, Development of an intelligent multisensory chatter detection in Milling, Mechanical Systems and Signal Processing, 23 (5), pp. 1704-1718

[27] Budak, E., and Kops, L., 2000, 'Improving Part Quality in Milling of Titanium Based Impellers by Chatter Suppression and Force Control, CIRP Annals Vol. 49(1), pp. 31–38.

[28] Zuperl, U., Cus, F., Milfelner, M., 2005, "Fuzzy Control Strategy for an Adaptive Force Control in End-Milling", Journal of Materials Technology 164-165, pp.1472-1478

[29] Haber R.E., Alique J.R., Alique A., Hernandez, J., Uribe-Etxebarria R., 2003, Embedded Fuzzy Control System for Machining Processes. Results of a case study, Computers in Industry, Vol. 50, 353-366

[30] Kim, T-Y, Jongwon, K., 1996, Adaptive Cutting Force Control for a Machining Center by Using Indirect Cutting Force Measurements, International Journal of Machine Tools and Manufacturing, Vol. 36, No. 8, pp 925-937.

[31] Sugita, N., et al, 2009, Dynamic Controlled Milling Process for Bone Machining, Journal of Material Processing Technology Vol., 209,pp. 5777-5784

[32] He, J., Pan, Z., Zhang, H., 2007, Adaptive Force Control for Robotic Machining Process, Proceedings of the American Control Conference, New York City, USA