Dawn of new machining concepts: Compensated, intelligent, bioinspired

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Publication date:
2018-06

Permanent link:
https://doi.org/10.3929/ethz-b-000311961

Originally published in:
Procedia CIRP 77, https://doi.org/10.1016/j.procir.2018.08.194

Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 77 (2018) 1–17

www.elsevier.com/locate/procedia

8th CIRP Conference on High Performance Cutting (HPC 2018)

Dawn of new machining concepts:

Compensated, intelligent, bioinspired

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Abstract

The impact of Industrie 4.0 onto machine tools is significant, despite the fact, that quite some of the novelties discussed within this new paradigm have their roots decades earlier. But especially the concerted action, which strives the development of sensors, controls, data processing together with connectivity, unprecedented data integration and the notion of cyber physical production systems open up new development lines towards manufacturing systems as enablers for the progress in manufacturing. Highly developed compensation concepts are developing into state depending AI-supported strategies. Maintenance becomes predictive, as learning of machines becomes global and model based. Further inspirations taken from biological systems are adopted for machining centres and drive a biological transformation of manufacturing machines. Machine intelligence becomes the basis for executing manufacturing processes, which requires a close integration of process intelligence (CAM-systems) and machine controls.

Keywords: Biologicalization, Industrie 4.0, Cognitive Technical Systems, Machine learning Strategies, Bioinspired, Biointelligent Manufacturing, Adaptive Thermal Compensation, Self-Organization, Self-Healing, Sensors in Abundance

1. Introduction

In the past 10 years it became obvious, that manufacturing provides the basis for a stable society. 20% of GDP as industrial production or 25% as production of tangible goods seems to be the basis of wealth even in a service oriented society. In the end, all thoughts of engineers have one unique dedication, namely to provide products to fulfill requirements of mankind. Therefore, it is not only money, that makes the world go round, but production machinery. The modern world is populated by about a new value of 350 billion $ of CNC driven machine tools, which is approximately 2.5 million CNC machines. As shown in Figure 1 each year a value of 50 to 60 million CNC machines is added, still increasing the population of CNC machines, because some of them replace non-counted non-CNC machines. Approximately 2/3 of them are cutting machines.

In 1951, the CNC control has already been invented, being one of the most groundbreaking developments in production machines, but the transition is still on its way. According to [47] from 2018 to 2025 the population of CNC machines in Europe will increase from 700’000 to 800’000, while non CNC-machines will strongly decrease in number. Since then the overall increase in productivity, which according to [58] is approximately 2 to 3% per year is basically supported by an incredible amount of ameliorations and better exploitation of the technology. Just as an example: a tool segment for the tire industry produced on one of the old punchtape based machines would require 1000 kg of punchtape, which moves this production clearly in the vicinity of technical overkill at that times. Figure 2 shows for a gear grinding machine the overall increase in productivity over the years, driven by enhanced process technology, enhanced tools, machine tool development being capable to withstand higher forces and vibration excitation, faster controls, more powerful drives, sensory, and better automation. Naturally also set point generation has largely enabled higher cutting speeds and it can be estimated that in case of more reliable cutting

10.1016/j.procir.2018.08.194

materials and better tool benign tool paths a reduction of production time in the two-digit percent range can be achieved. Within CIM in the 80s and 90s an attempt was made to automatize the strategy planning, an intelligence or experience requiring act within the process chain of cutting. This was not successful due to limited computational power and economic interests. In the meantime, additive manufacturing still in the stage of rapid prototyping showed the possibility to start manufacturing only a few minutes after the workpiece geometry has been provided, which takes hours in case of cutting. To face the truth, produced parts in rapid prototyping lack several industrial requirements indispensable in the mature cutting technology. But the discussion on the notion of a “five-minute-machine”, requiring machine intelligence has been implanted.

Compensation, as kinematic, thermal gravitational or dynamic compensation is one of the achievements in recent times towards accuracy, reliability and robustness. The physical modelling behind are highly complicated, if they take into account all the essential influential effects within a machine tool. Models in use and scientific discussion spread from physical to phenomenological approaches, and in this range from complex and nearly unmasterable to simple while vice versa the parameter identification effort ranges from simple to awfully huge. Self-learning approaches based on some model seem to be the suitable work around for dilemmas like this.

Obviously, the human ability to take up pieces of information, store and combine them and take decisions on the basis of information from different times and environments is valuable in those cases of complicated and even complex behavior. Also other capabilities of biological systems besides cognition, learning capabilities and intelligence are highly desirable for machine tools and deserve research, such as machine autonomy, abundance of sensors, sensor fusion and redundancy, swarm intelligence and fleet learning, strong reliance optical image recognition, self-healing or wear and failure compensation and also teaching competence. Bio inspired structures are topics already introduced at least on the scientific level into machine tools as demonstrated in [41], which is insofar a fairly weak approach, as the condition of manufacturability needs to be taken into consideration, which today is only done by intuition of some designer. But for sufficient development of additive manufacturing for large structures a really topology optimized lightweight structure can be realized. Bio inspired functional surfaces for machine tools suffer from the fact, that these structures are extremely vulnerable and their lifetime is strongly limited. Biological systems always come up with self-healing capabilities, restoring the fine surface structures. Therefore, the capability for self-healing opens new potentials in very different aspects from tool sharpening to play filling, but is still in its infancy.

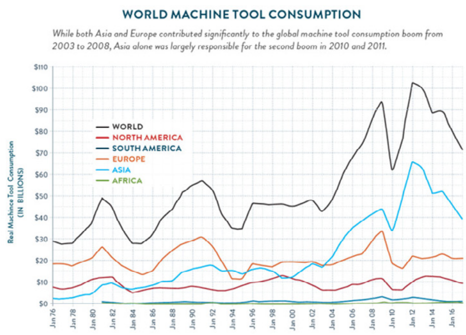


Figure 1: Increase of the machine tool population over time [60]

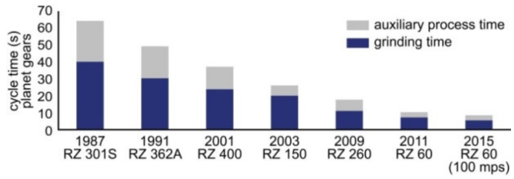


Figure 2: Reduction of manufacturing times (Courtesy Reishauer) [56]

2. Compensation

2.1. General remarks

Driven by accuracy requirements of machine tool applications the expenses for the mechanical improvements of machines by mechanical means are becoming more and more expensive. This requires a paradigm change which was attempted in several waves starting decades ago, namely to charge the control system with compensating for erroneous movements of the machine. These are always due to the fact, that positioning and position measurement of machine tool axes takes place far away from the TCP which shall be controlled and between those two the machine mechanics with its physically given insufficiency reigns. Several aspects today justify independent of earlier failures a reconsideration of this topic:

1.) A consequent design for compensation declaring repeatability as the highest principle has not yet been attempted [57].
2.) IT-technology of today offers drastically increased computational performance, especially if intensive number crunching required by the modelling approach is performed on the GPU (Graphical Processor Unit). Thus real time delivery of new compensation values becomes achievable.

3.) Huge investments of manpower have enriched the world with model order reduction algorithms of high and predictable precision as for instance demonstrated by [49].

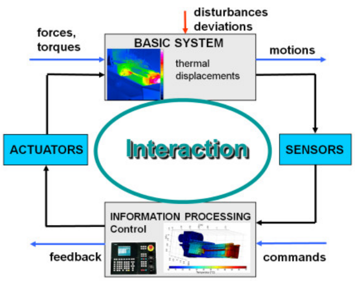
4.) Meta-modelling allows fast provision of new compensation values. Meta models also can be adapted on the fly to cope with changing machine and machining conditions. They are a preferred entry point of self-learning algorithms.

Compensation is done according to [57] to correct erroneous behaviour of the machine tool out of different reasons:

- Inaccurate kinematics
- Gravity of moving parts
- Dynamical deflection due to inertial effects as intalk, crosstalk, coupling forces
- Thermal displacements
- Wear status

While dynamical compensation needs extremely fast reaction or feed forward with the help of models, the other compensations are not requiring that high dynamics or are even static. Compensation requires models of the machine tool and / or the process, in order to take effects into account, that happen during the long life time of a machine, those models become extremely complicated and complex, self-adaptability and machine learning become of crucial importance as will be shown in chapter 3.

2.2. Thermal compensation



Sensor technology	Modelling	Actuator Technology
NC-program	Physical field equations	Cooling, heating
Power intake of components	Reduced physical field equations	Axes of machine
Temperature measurements	Thermobalance models	Additional axes
Elongation measurements	Phenomenological models	
Position measurements	KI approach, neural networks	

Figure 3: Mechatronic concept of thermal compensation and morphological box [57].

As stated by Mayr *et al.* [35], thermal errors are by far the most prominent source of manufacturing errors, and because thermal compensation has less time restrictions and thus really becomes industrially viable, it is elaborated to more detail. The standard means to cope with thermal elongations in high precision machining is to create a thermally stable environment by air conditioning of the shop floor and by run in to get a stable distortion or tempering the machine to mitigate thermal gradients. The energy consumption of machine tools is under discussion for over one decade, and becomes more and more suspiciously observed. With the aspect of knowledge based machining the modern approach is to go for a thermal compensation, where the machine tool axes execute the error corrections without any utilization of further power as in the cooling and air conditioning approach. Thus, not only from the accuracy perspectives, but also from the energy efficiency perspective, there is no way around thermal compensation. Figure 3 shows different ways how to setup a thermal compensation action chain. Knowledge basis is the model which takes up data from the basic system by sensors and changes with the basic system with the help of actuators. Everything that supplies information to the compensation intelligence is considered as sensor. This can be displacement measurements, thermal measurements and also the CNC program is considered as a sensor. Actors can be a chiller, the machine axes as well as auxiliary positioning devices. From top to bottom the models become less physical, which on practical basis means that its modelling complexity as well as the computation time is reduced to become more and more real time capable. This needs to be then counterbalanced by measured parameters displaying the complexity of the system and thus the calibration effort needed to setup the model in the beginning is increasing from top to bottom.

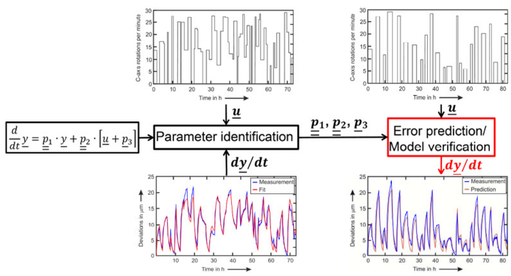


Figure 4: Procedure of phenomenological modelling, calibration and compensation [57].

Figure 4 displays the procedure for phenomenological modelling with sensor input from the CNC program. As basic system the rotary axes block of a 5-axis milling machine is used. As phenomenological model a fairly crude representation of the physics of thermal behaviour is used, keeping only the history dependency of errors on the movements of the machine as physically correct representation. Similar modelling has been presented e.g. by Mayr *et al.* [34], Yang and Ni [64] and Brecher *et al.* [7]. This gives a system of first order differential equations as shown in Figure 4 for the location error vector $\underline{y}$ of the rotation axes depending on the vector of thermal inputs $\underline{u}$ which contains the power inputs of the axes, environmental temperatures etc.. All the elements of the matrices $\underline{p}_1$, $\underline{p}_2$ and vector $\underline{p}_3$ need to be then identified during a calibration cycle.

This calibration cycle consists of 70 hours of randomly chosen movements of B- and C- axis. The displacement ZOT of the table surface in vertical direction as an example for one of the components of the vector $\underline{y}$ is shown in Figure 4 as simulation result together with the measuring results, which show expectedly good accordance, because for this motion the parameters have been identified.

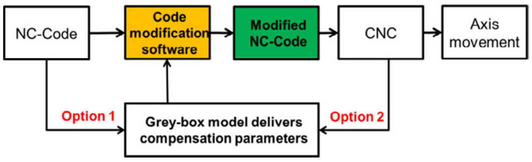


Figure 5: Block diagram for thermal compensation [19]

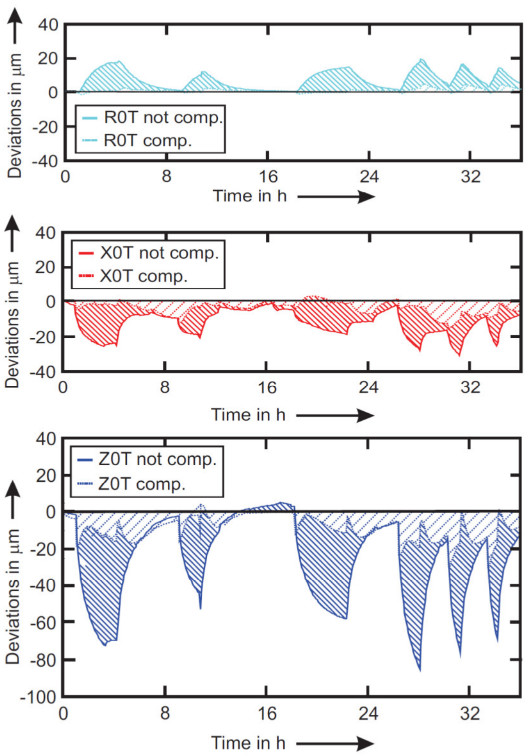


Figure 6: Achieved compensation results with the phenomenological model [57]

To verify the model to more than only suitability a different randomly chosen motion profile for B and C is evaluated with the model and measured as well. Again, the model represents very well the measured behaviour of the machine and the simulated error values can then be used for compensation according to Figure 5. Figure 6 then shows the achieved compensations, which demonstrates that this kind of modelling is clearly capable to serve as a model for online compensation of machine tools.

The scientific questions still open are, how short a calibration cycle might be to achieve a given quality of compensation and what happens for very long run times or changes in the mode of utilization of the machine. For the latter, a solution is provided in chapter 3.

3. Autonomous machine learning

3.1. General remarks

Learning is a fundamental element of Intelligent Manufacturing Systems (IMS), and closely linked to the notion of Biointelligence. Learning processes in general can be classified in three categories, depending on the available feedback: Supervised learning, reinforcement learning and unsupervised learning.

Supervised learning postulates that the desired outcome (solution) is available together with the respective data. Reinforcement learning provides an evaluation of the solution given by the learning algorithm, usually of qualitative or binary nature. The unsupervised learning process does not provide any (external) solution [37]. The solution lies within the data, usually referred to as a structure. It is usually used to cluster and trim datasets, such as automated outlier detection for instance. The notions of other learning types, such as fleet learning, deep learning and model based learning are specific applications of supervised, unsupervised or reinforcement learning. Hybrid approaches of the previously named approaches are possible, and practically applied in many of the presented cases (e.g. [6,31]). Fleet learning is a term derived from condition monitoring applications in aircrafts, and has also found applications in automotive autopilot training [51]. However, it has not yet been published in conjunction with manufacturing related approaches. Model-based learning defines any learning approach relying on pre-installed knowledge (pre-taught patterns, inclusion of expert knowledge), showing a larger and faster learning success. It can be considered as a Funnel of Nuremburg for Machines. Internal research at IWF (ETH Zurich) hints that model-based learning is also a useful measure to compensate for low-quality low-quantity historical data for the training of appropriate models. As a complete overview over all machine-learning techniques goes beyond the scope of this report, the reader's attention should be drawn to [62] for an in-detail overview of machine learning approaches in manufacturing and their particularities.

3.1.1. Learning with structured and reliable data

Learning approaches are mostly characterized by the quality of the relevant and available data. A plethora of high quality datasets registered over appropriate timespans is a rather rare case, wherefore few successful applications of unsupervised learning approaches in manufacturing have been published. One of the few exceptions that provided an application for unsupervised learning algorithms in manufacturing was published by Lieber *et al.* [30] in 2013, using unsupervised learning for preprocessing and feature extraction purposes of datasets generated in a rolling mill. Luckow *et al.* [31] described in 2016 the possible application of unsupervised learning for visual inspection processes in manufacturing, as well as for recognizing features in camera images of robots enabling self-learning techniques. For the visual inspection process, a large database of already-existing imagery was used in order to train the algorithm, therefore circumventing the issue of collecting the data manually. However, an important aspect here is the notion of transferring learning from one case to another, which is also applied by [40] and [45]. In [45], the fusion of knowledge of manufacturing operations data is carried out by representation learning. Representation learning describes a learning method in which the feature set is auto-discovered by the learning algorithm. The feature engineering or extraction is carried out automatically.

Even if data becomes more and readily available, and processing tools and units decrease in cost while they increase in performance, the collection of the right data within a sufficiently defined context at the right time in a sufficiently large quantity remains an issue [31]. As for the design of learning approaches, this challenge is not always easy to overcome. Reinhart and Steil [44] go as far as suggesting hybrid approaches for inverse kinematic controls of robots. According to their findings, parameter identification remains less cumbersome as the data collection for a pure machine-learning approach. The machine learning approach is used to model only complex characteristics outside of the identified parametric model. The combination of physical and statistical modelling however is not an isolated case, as underlying physical models can be used to decrease the need of generated data for proper results. Together with the transferal of already acquired knowledge in different applications, these hybrid approaches appear to be a valid approach for a learning approach in manufacturing, given a lack of available or accessible data. As some sort of physical knowledge is always used at the foundation, most approaches can be considered as hybrid. However, the degree of hybridity differs severely between most known approaches of learning strategies in manufacturing.

To our knowledge, transfer learning in a direct manufacturing context has not been published yet. However, it is widely used in image recognition in conjunction with Convolutional Neural Networks (CNN) [43]. As CNNs train different layers for subsets of image recognition (e.g. identification of vertices and edges), layers can be reused for different purposes, considerably lowering the necessary training data set volume. The underlying principle of data clustering and analysis remaining the same, only the mapping to predefined objects or states (e.g. conform or non-conform pieces) needs to be trained when applied to manufacturing systems.

The supervised learning approach is by far more frequently used than the non-supervised learning approach. Denkena *et al.* [11] implemented a support vector machine approach in 2016 in order to create a self-optimizing cutting process. The obtained process data is continuously modeled, in order to optimize the cutting parameters for the satisfaction of predefined boundary conditions. Wuest *et al.* [61] used a supervised machine learning approach in 2014 for product quality monitoring. Product and process states were introduced in order to partition the manufacturing program into sequences, allowing for a standardized data collection. This ultimately enables a "collection of data across a wide spectrum of product and process information". In 2016, Haas *et al.* [23] proposed an iterative learning control approach to reduce systematic tracking errors in machine tools. In 2017, Arinez *et al.* [2] demonstrated the use of reinforcement learning in order to train a gantry scheduling policy, allocating material two a buffer serving two machines at once. The trained manufacturing cell showed a significantly lower production loss than the previously installed first-come-first-serve approach. Escobar and Morales-Menendez [13] published a machine learning and pattern recognition technique in 2017, allowing to detect defective welds from an ultrasonic metal welding process. Another interesting application of supervised machine learning in manufacturing was introduced by Shin *et al.* [50] in 2014: By the combination of STEP-NC features with NC data extracted via MT

Connect, a model was trained which could predict the power consumption of machine tool. However, the performance was rather low, with a prediction error in between 11% and 21%, depending on the material used. The here within presented example of the autonomous and adaptive thermal error compensation by Blaser *et al.* [6] accordingly falls under the definition of supervised learning with structured data. Summing up the use of the so-far discussed machine learning methods, the limits of the application seem to lie in the challenge of an automatized collection of structured and reliable data.

3.1.2. Learning with unstructured, imprecise, fuzzy or probabilistic data

However, cognitive systems should be able to learn based on uncertain or probabilistic data. Additionally, associative learning (transferring knowledge from one case to a different setting) as a method of creation of new knowledge, can be considered a trait of advanced cognitive systems. Moreover, learning and adaptation based on experts' advice, as well as learning on rather gray and fuzzy instructions by a worker for instance, are also learning strategies that should be considered.

An example for the learning with unstructured data is the creation of a clustering or standardization framework: In 2014, Wuest *et al.* [61] designed specific conventions, in order to allow for a standardized learning cycle, yielding favorable results. They defined a set of characteristic product states, allowing to measure and cluster data, as well as detecting and classifying changes in product conditions.

In the context of learning with unstructured or imprecise instructions, the notion of fuzzy control, or fuzzy learning comes to mind. This describes the ability of the machine to properly interpret a qualitative input, usually by a human interaction. [13,37,61,62] made use of, referred to or mentioned fuzzy control in their respective publications.

Telling from the variety of different learning approaches used in the publications cited in this chapter, the absence of robust, efficient general learning approaches becomes obvious. There currently is not a one-size-fits-all measure, but it seems as if learning approaches are surprisingly diverse. As the handling of system changes over time, a current and certainly future focus is the (self-)adaptation of algorithms, as presented for instance by Blaser *et al.* [6] in chapter 3.2.

An open question waiting for answers is the optimality between modeling and learning effort. It might differ considerably with the application cases (and with available data quality and quantity), but a general framework is yet to be developed. This is also interesting in the context of using similar models in different situations, where the results need to be scaled for comparison (i.e. application of similar learning approaches to different machine types). As internal research from IWF (ETH Zurich) hints, the modeling effort rises considerably with the application of similar learning strategies to even slightly differing machine types.

With the increase of high volume high quality data, the modeling effort decreases. However, a main problem remains to acquire sufficient and reliable data, especially for unsupervised learning approaches. Furthermore, the utilization of data from other machine types in transfer learning cases lacks model applications and guidance. This issue hints at a further development of fleet learning as used by Tesla Motors in order to answer the question of comparability between data from different machine sizes and types. Summing up the previous argument, the notions related to associative learning (transfer learning, fleet learning) should be elaborated more in-detail in manufacturing contexts.

Alternatively, successful and universal approaches of introducing unreliable and unstructured data are of interest. Beneficially might be to pursue the question of registration and evaluation of each and every input of a skilled and virtuous user, so that implicit knowledge can be made visible. It becomes evident that the combination of rule and model based expert systems with learning capability enhances manufacturing processes.

3.2. Adaptive learning control for thermal compensation

As pointed out in section 2.2 models for machine tool covering their full behaviour become infinitely complicated. Reduced models combined with machine learning is therefore here considered as superior. Especially the integration of history dependent power input data, the modelling of time delays introduces errors on the long run of a machine. Mou and Liu [38] pointed out, that working conditions might change such, that the identified parameters of the simplified phenomenological model are no more suitable. Starting with the model explained in section 2.2 a self-learning algorithm, developed by Blaser *et al.* [6], as adaptive learning control (ALC) can be established as sketched in Figure 7. This method requires an active thermal displacement modelling, which predicts the thermal displacements, transfers the correction data to the machine control via some provided interface as FOCAS2 of Fanuc, which is then used for correcting each individual axis. From time to time measurements of real data from the machine take place to compare the predicted

displacements with the actual displacements on the machine. For this compensation scheme only providing the relationship between displacements and heat inputs, no other than position measurements can be used for this, which means that a defined geometrical object needs to be placed on the work piece side and a probing system on the spindle system is used to determine the position of this geometrical object. As most machine tools today provide an exchangeable probing system, this is used to probe a precision sphere positioned 160 mm outside of the center of the C-axis in 4 different positions of the C-axis as also shown in Figure 7. These measurement values are then used to recalibrate the parameters within the matrices and vectors of the model equation.
The principle of mitigating thermal errors is then presented in Figure 8.

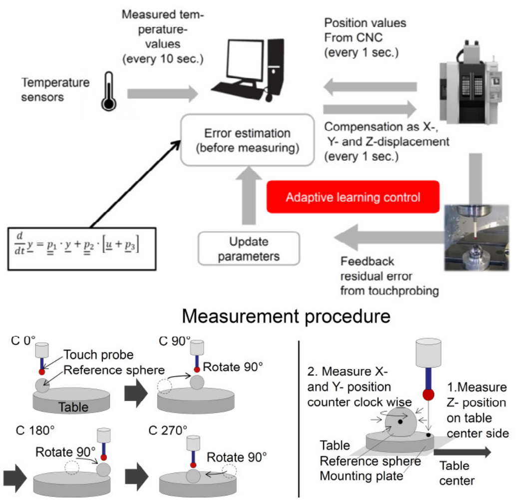


Figure 7: Principle of adaptive learning control for thermal error mitigation in machine tools in the bottom is shown the measurement procedure [6].

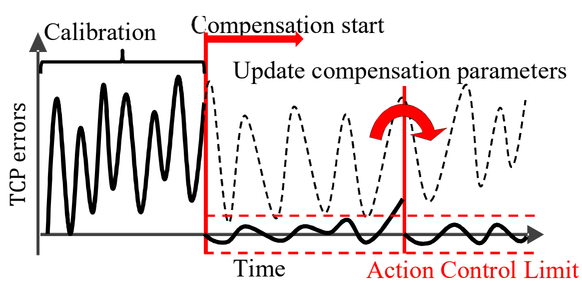


Figure 8: Illustration of the concept of ALC for thermal error compensation, adapted from Blaser *et al.* [6]

The effect of ALC is shown in Figure 10 for the machine tool with V [w C2' B' b [Y1 Y2] X [Z1 Z2] (C1) t] as kinematic chain according to ISO 10791-2 shown in Figure 9. The first calibration is set to a reduced time interval of 12 h, which is typical for run in times at the machine tool maker. The correlation between achieved location errors and run in times is shown in Figure 11 for a situation with thermally stabilizing cutting fluid and without. It can be recognized, that depending on the cutting fluid supply the calibration times exceed these 12 h strongly. Despite 12 h seems to be too short for a good calibration, it is applied here to demonstrate the effect of ALC. Here the thresholds for recalibration are set to 15 µm for linear and 25 µm/m for rotational axes. The system starts with 30 min between each recalibration. When these thresholds are surpassed, the recalibration times are automatically reduced to 15 min and a time delay of two hours is set for the application of new data, to have sufficient measuring points for the recalibration. Figure 10 shows, that the ALC approach is suitable for enabling compensation with limited accuracy models.

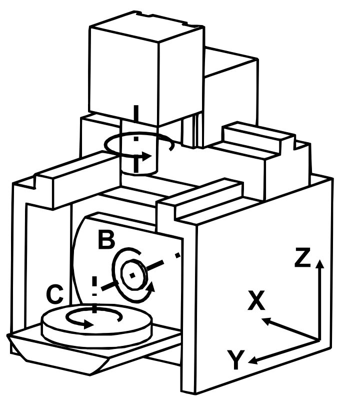


Figure 9: Structure of the investigated machine tool

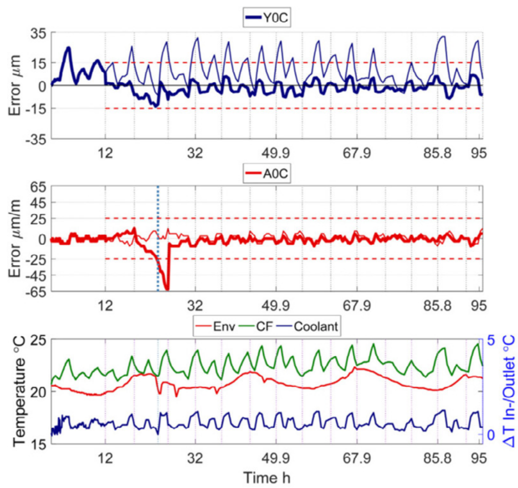


Figure 10: Results for the thermal compensation with ALC approach

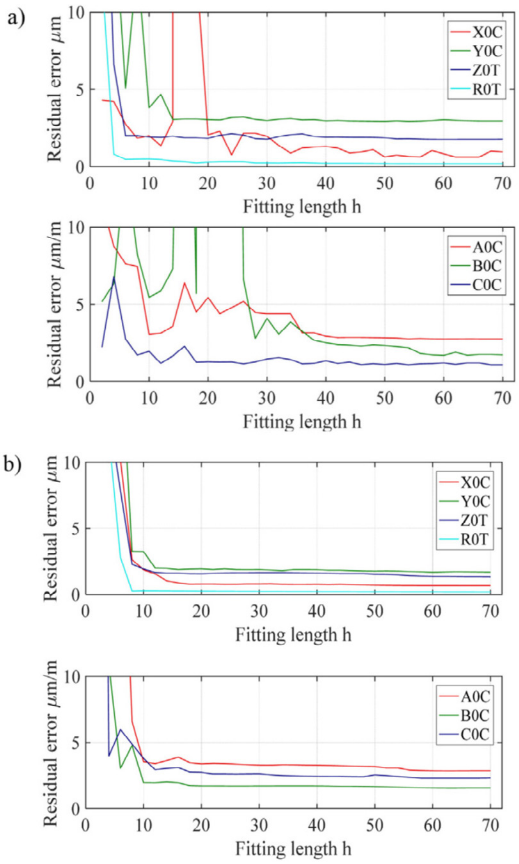


Figure 11: Correlation between the calibration time and the achieved location errors. Without cutting fluid in a and with stabilizing cutting fluid in b [6]

Drawback of the method is the necessity to perform position measurements, which are time consuming as they cannot take place parallel to machining. Reconstruction of the model such that temperature measurements at specific points within the machine can be used instead is at the moment under preparation. More elaborate learning algorithms are developed to change the structure of the model if required. Deeper reconstruction of the model, even change of thermal sensor placement is possible with a machine learning approach, but anyway requires rules and algorithms for those modifications to be predefined.

3.3. Iterative learning control for path planning

The concept of iterative learning control can also be applied for the increase in accuracy of tool paths in machining, which was reported in [23]. Difficult for this task is the limited bandwidth of typical motion controllers, which therefore requires feedforward control with knowledge out of previous trials. Fast exploitable models per axis with limited physical exactness are used as shown in Figure 12.

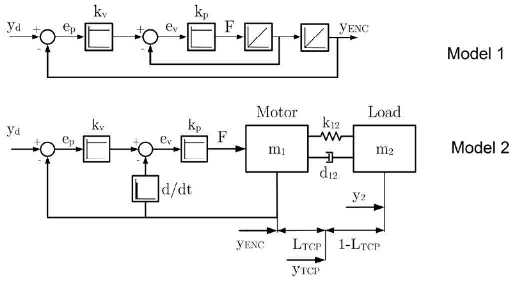


Figure 12: Single axis models of limited physical accuracy used for estimation of the TCP position [22]

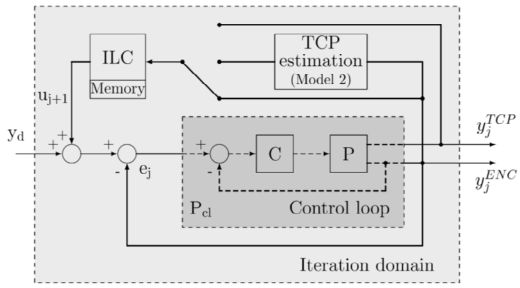


Figure 13: Block diagram for the ILC for path planning containing three different feedback possibilities: (1) feedback from the encoder signal directly, (2) feedback from an estimation of the TCP out of model 2 and the encoder signal (3) feedback from direct measurement of the TCP with an external cross grid [22]

For the feedback either the encoder signals are exploited or an external measurement system directly tracing the TCP is used for the learning feedback. The latter possibility is not suitable for practical utilization in real manufacturing, but shows which accuracy increase is possible, if exact knowledge of the TCP movement were accessible. With the encoder signals an estimation of the TCP movements with the help of the two-mass model from Zirn [68] is used instead of a measurement at the TCP. Thus, the scheme of the ILC for path planning containing three different possibilities of setup of ILC is presented in Figure 13.

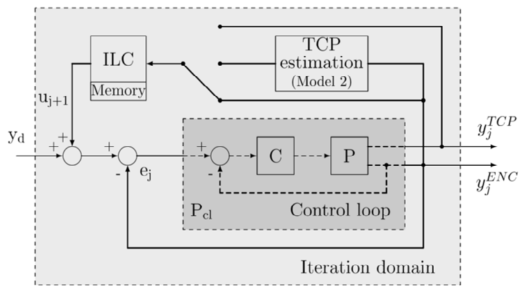


Figure 13

Figure 14: test bed for the validation of the ILC algorithms for path planning

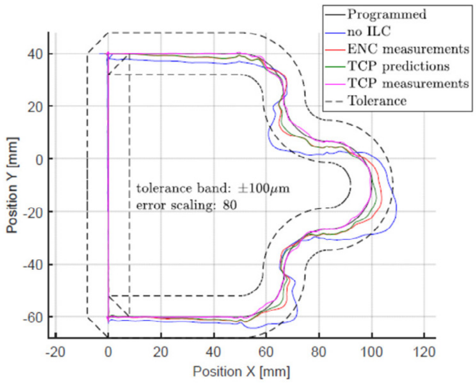


Figure 15: contour accuracy of three different ILC schemes [22].

For the test bench from Figure 14 the results of the ILC for a chosen path and the three different learning approaches is presented in Figure 15. Naturally the feedback of exact TCP data enhances this ILC best, but the simple models for the prediction of the TCP behaviour depending on the commanded paths show respectable increase of path accuracy and in this case, bring the TCP over the whole prescribed path within the tolerances.

Depending on the iteration scheme, only very little numbers of iterations are required until the final accuracy of the path, which makes this feasible for repetitive manufacturing tasks. A generalization to unknown manufacturing paths, where training for a feedforward is not possible, the learning algorithm is capable to learn frequently repeated sections or features of paths, which can then be stitched together to give an enhanced TCP path. This approach specifies a self-enhancing expert system for path planning on a specific machine, which can be setup without intense modelling of machine structures.

4. Expert systems and teaching machine

Expert systems on machine tools comprise the available knowledge of how to run the process. The only way how "keep it simple" works in those cases is, to hide the full physical complexity of the process the user and let the expert system on the machine do the work. But nevertheless, for machine tools experienced users outperform any expert system as they have for special applications specialized knowledge and therefore need to have the access also to all details and parameter selection. Especially for strongly experience based processes as it is the case for grinding and EDM expert systems are offered within the machine, which is the basis for creating intelligent machines. The TechnologyIntegrated solution by Fritz Studer AG (Thun, Switzerland) [17] is an example. Here, an expert system was designed, in which previously digitalized knowledge is used to automatically assess a near-optimal parameter set for a grinding process. The worker is then instructed by the system on how to setup the process and the grinding parameters are automatically selected from the expert system. As shown in see Figure 16 the expert system ranked among the three fastest workers which showed a fulfillment of a 100% of all requirements. On the other hand, this demonstrates the headroom for improvements if the system is capable to learn from experienced users as shown in Figure 17. The machine becomes the main information storage and for this concept needs to have close contact to technological data bases, if these are not directly stored within the machine control. In this learning and teaching approach the machine directly behaves like a biological system. An interesting question in this respect is, how the machine control distinguishes between the apprentice and the master.

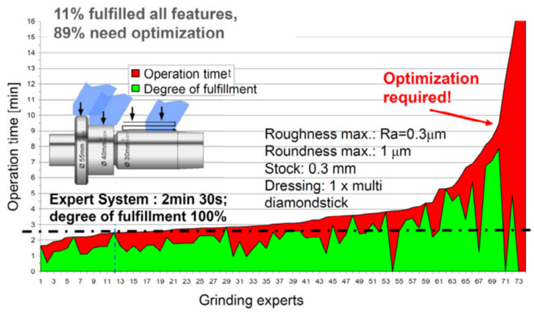


Figure 16: Performance of the Studer TechnologyIntegrated solution in comparison with the performance of human experts for a dedicated grinding process [18].

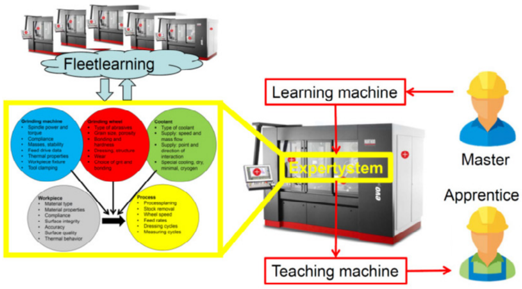


Figure 17: Learning and Teaching Machine.

5. Self-Healing and Self-Organization

An important trait in the biological transformation is the ability to handle exceptions, in which the system needs to adapt to disturbances, partial or complete breakdowns. By comparing the way how systems treat possible failures, a distinct line can be drawn in between self-organizing and self-healing systems:

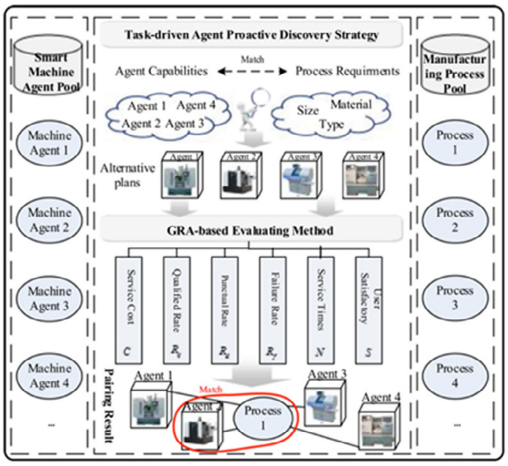


Figure 18: Task-driven Self-Organizing Model [67]

Self-Organizing Systems: Systems that have a larger space of possible solutions (including a defined set of disturbances), which can swiftly switch to a different solution in case of a detected misbehavior or failure. An example would be a manufacturing system fulfilling an optimization problem, in which multiple solutions are optimal, and can be selected arbitrarily, such as in [67] and presented in Figure 18. The systems are defined as self-organizing systems, which are able to adapt to changing conditions by the selection of different available elements or different process sequences to be used. This does not include repair of the defective or misbehaving unit or fraction, but a mere mitigation of defects of member entities. An example referring to machine tools would be the autonomous detection of a precision loss incurring within a section of a ball screw, and the subsequent shift of the process window outside of the section suffering from precision loss. Self-Organizing systems can be characterized by

- Predefined disturbance and solution sets,
- problem circumvention (redundancy, diversity) rather than root cause elimination,
- the lack of ability to reconstitute an original, desirable state,
- and cognitive capabilities limited to detect symptoms belonging to the predefined solution space.

Self-Healing Systems: Systems that are able to reconfigure, identify and repair autonomously following a misbehavior, failure or error. Systems fulfilling the following characteristic traits can be defined as an actual self-healing system:

- A priori unbound disturbance and solution space,
- retention of a functional state not entirely dependent on redundancies,
- ability to reconstitute an original desirable state,
- distinct cognitive capabilities allowing to intrinsically or heuristically develop solutions to a previously undefined disturbance.

From software development, an analogous definition of necessary traits can be drawn. They include consistency-maintenance mechanisms, failure-detection techniques and recovery techniques [10,16]. Self-Healing Systems require a large array of sensors in order to allow for the necessary cognitive capabilities to detect disturbances and unwanted behavior. [21] gives an overview of appropriate monitoring approaches as enablers for self-healing methods in machine tools.

5.1. Self-Organization

Matt [33] introduced a theoretical framework in 2012 which relies on axiomatic design principles, and implements "[passive] self-healing mechanisms in agile production systems". The basic self-organizing strategies are described as redundancy, diversity and detection of system failures.

The modelling of the self-organizing energy harvester by Farnsworth & Tiwari in 2015 [15] is a prominent example of a self-organizing mechatronic system. It exhibits failure management systems allowing to regain functionality by redundancy for some specific and anticipated failure cases. In the same manner, Benkhelifa *et al.* [5] proposed a design of electronic circuits in 2013, in which faulty lines are eliminated and an alternative path fitting to the functionality is sought (Figure 19).

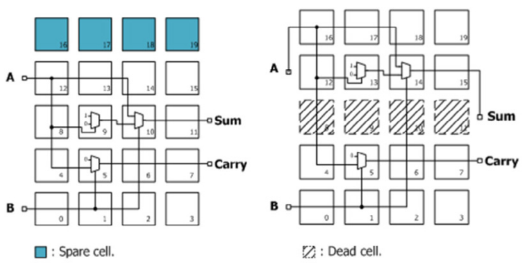


Figure 19: Self-organizing electronic circuit as proposed by Benkhelifa *et al.* [5]

Another interesting case, falling under the definition of self-organizing systems, is the conception of a self-healing epoxy composite containing Hexamethylene Diisocyanate (HDI) capsules, proposed by Khun *et al.* in 2014 [27]. The application field is frictional abrasion and wear compensation by HDI-filled microcapsules, which form new layers on the wear track when disrupted. The system was developed with respect to the tribological surface properties, making it a useful application also for functional surfaces. A similar approach for the internal repair of epoxy coatings by the use of Tung Oil was proposed Samsdzadeh *et al.* in 2011 [46].

As the application of self-healing surfaces can be extended to many different research fields, research of different aspects and possible applications have been published over the course of the past 15 years. For an in-depth review of the fundamentals and earlier achievements of self-healing materials, the reader's attention should be drawn to [59].

Likewise, concerning the more recent developments on metal matrix composites including self-lubricating and self-healing aspects, Moghadam *et al.* [36] published in 2014 a comprehensive review of function and performance, as well as an outlook. They highlight the difficulty of healing metallic materials compared to polymers, given their material properties. As an approach pointing rather towards the self-healing category, they also consider the use of Shape Memory Alloys that recover after heating.

5.2. Self-Healing

First of it all, it should be noted that very few publications are currently available that directly concern the use of self-healing technologies in manufacturing systems. Therefore, an overview over recent publications in the field of self-healing technologies, and their possible uses in manufacturing will be provided.

In 2014, Jiang [26] proposed a bio-inspired self-sharpening cutting tool surface, which applies shark-teeth like architectures to hard turning of steel tools. The performance of the proposed structures yields longer tool life, and higher surface qualities than comparable benchmark solutions. The only other mentions of proper self-healing systems were not found directly as integrated parts of manufacturing systems, but can serve as exemplary blueprints for later applications in manufacturing systems: Murata *et al.* [39] demonstrated their fundamental research work on self-repairing systems, consisting of both component and functional healing. The work includes hardware designs of two- and three-dimensional mechanical units and algorithms for self-assembly and self-repair.

Bell *et al.* [4] confirm in 2013 the absence of a universally-accepted notion of self-healing and self-repair. They distinguish self-healing and self-repair in the way that self-repairing system can "partially or fully fix a given fault to continue operation", whilst self-healing systems are able to "bring themselves back to its initial state of operation after a fault has occurred". They also insist on the fact that different research fields (mechanics, electronics, software) bring different meanings to the terms, which leads to further confusions. No practical applications or prototypes are proposed. In a subsequent publication, Bell *et al.* [3] propose the concept of a self-rectifying 4-bar linkage system. The authors criticize the higher complexity, inevitably leading to a less reliable system, possibly hindering the harvest of the full fruit of self-healing techniques.

Levi *et al.* [29] proposed a lab-case of a swarm of reconfigurable robots with self-assembling, and intended self-healing capabilities. They tried to prove the applicability of cognitive capabilities, including situation-awareness and decision-taking. While the mere re-organization of a swarm of robots falls under the definition of self-organization, the cognitive capabilities and the strive to repair and reconstitute the original state of swarm members corresponds to the definition of self-healing. However, many challenges in terms of complexity, both hardware and software alike, could not be overcome at the time of publication (2014). The authors mention that with learnings from the Human Brain Project (HBP), the gap to train artificial robot genomes after the human brain controls could be closed.

In general, "data-healing" could also be classified as a self-healing system in the context of manufacturing. Fault detection, isolation and recovery (FDIR) techniques have been applied in software applications for a while. The creation of redundancy and backups on memories help to recover (partial) data loss, while the system excludes faulty parts from further use. This principle can be applied also to general data processing units, e.g. in sensors, like Yang *et al.* [63] presented recently. The key is the self-creation of the necessary redundancies on available capacities. As the faulty parts of a memory usually cannot be recovered to its initial state, FDIR systems are ambiguous in the definition of self-organizing and self-healing systems. To a certain extent, data loss is always recovered and brought back to an initial desirable state (self-healing), while the hardware aspects used can be described as self-organizing.

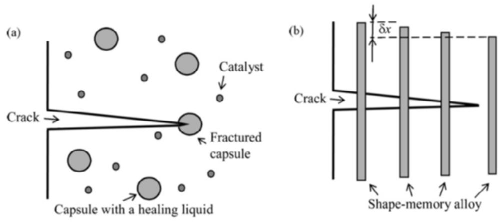


Figure 20: proposal of a Self-Organizing (a) Liquid Capsule based Material Repair, and a Self-Healing (b) Shape Memory Alloy based Repair [42]

When referring to self-healing, surface reconstruction such as skin reconstruction or plant surface construction immediately comes to mind. Similar principles have been investigated: A possible application case for self-healing compensating wear-out of surfaces was published by Nosonovsky & Bushan [42] in 2010 and is shown in Figure 20. It contains a discussion of the fundamentals of bio-inspired self-healing technical surfaces, as well as most general self-healing mechanisms for surfaces.

Examples presented with a potential use in manufacturing are surface crack healing techniques using micro capsules containing a liquid or reinforcement of crack voids by shape memory alloy demonstrated in Figure 20. The first notion can be considered self-organization (as the liquid will be missing in other places, potentially weakening the structure), whilst the shape memory alloy reinforcement is closer to the definition of proper self-healing.

Another interesting aspect of self-healing aspects is introduced by Farnsworth *et al.* [14] in 2015: An autonomous maintenance system for through-life engineering. Here, the ideal aim is to conceive a system which predicts its need for maintenance and carries out the process autonomously. The emphasis lies on the autonomous execution of the repair task, as it would otherwise correspond to a mere condition monitoring or predictive maintenance system, which is the indispensable prerequisite for Self-Healing systems. This definition was first formulated by Amor-Segan *et al.* [1] in 2007, that is "the ability to autonomously predict or detect and diagnose failure conditions, confirm any given diagnosis, and perform appropriate corrective intervention(s)". Another publication corresponding to this premise is the adaption of Prognostics and Health Management (PHM) principles to manufacturing environments, denoted as Engineering Immune Systems by Lee *et al.* in 2011 [28]. The approach of resilient and self-maintenance systems also seems like a promising approach for future research.

However, no system is fail proof, given the uncertainty which is at the root of most errors. This uncertainty is hard to cope with, given that current Self-Healing approaches include only anticipated and foreseeable failure cases. Farnsworth *et al.* [14] propose that the combination of their autonomous maintenance approach for robotics with other passive self-healing theories (e.g. Design for X) would yield favorable results. Design for X (DfX) is a term defined by [12] among others, designating a design philosophy focusing on a design around a certain parameter (set). Typical examples are Design for Assembly, or Design for Maintenance. In the specific case, Design for Maintenance, Design for Reliability, and Design for Self-Healing are mentioned, enabling self-awareness, preventive and reactive capabilities of the system. Again, it becomes clear that Self-Healing is currently limited by its specific and foreseen application context. One may argue that biological systems are also limited in their resistance to unforeseen disturbances, however, Associative Learning can help overcoming some of these boundaries. Additionally, Design for Self-Healing as mentioned by [14] implies other DfX, and lacks a concise definition. In future research scenarios, a profound and complete definition of this approach can be considered helpful.

5.3. Self sharpening tools

Several examples of adoption of properties and behaviours of biological systems exist. Famous are especially the properties of biologically inspired surfaces, where a good survey of technologies is collected in Malshe *et al.* [32]. An artificial reproduction of those surfaces yields the effect observed on the biological system. But contrary to biological systems the artificial ones are incapable of a self- healing or regrowth of worn parts of the surface. For example, superhydrophobic surfaces as shown in Figure 21, being manufactured by laser or EDM have the same structure as the lotus leaf, namely a nano structure superposed onto a structure with structural lengths in the 10 μm range, where the microstructure can also be discovered in Figure 21, while the nanostructure are the laser ripples inevitable with ultra short pulsed lasers. Interest exists to use this for machine tools to repeal coolant from the surfaces. Touching this surface damages the fine structure very fast, which decays the effect.

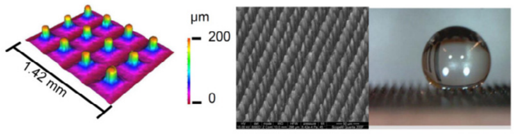


Figure 21: Superhydrophobic surface manufactured by laser

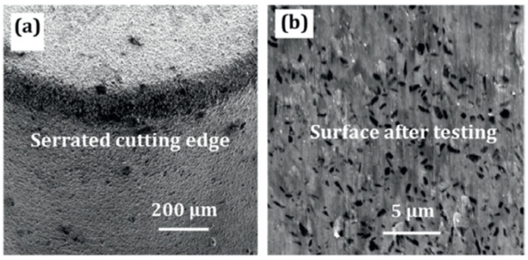


Figure 22: permanently stable serrated tool surface with the help of CBN – TiN composition of the coating by [32]

All technically usable functional surfaces must be designed such, that the structure is reproduced directly by the expected wear attack, might it be mechanical or chemical. Such a functional surface is presented by [32] and in Figure 22. The wear reduction due to the serrated surface of the tool is reproduced by mechanical wear attack, as the embedded hard particles (CBN) repell the wear attack to the softer areas (TiN) in between and thus stay as new protruding tips above the surface. Whenever they become removed another particle emerging out of the bulk of the TiN-coating takes over the load. This is a new approach for geometrically defined cutting edges but the long used principle of self-sharpening of grinding wheels. This example shows clearly how technical systems must be equipped with a reserve of vitality to deal with wear that continuously removes parts from the surface.

Figure 23: Archetype for self-sharpening tools: the beaver tooth

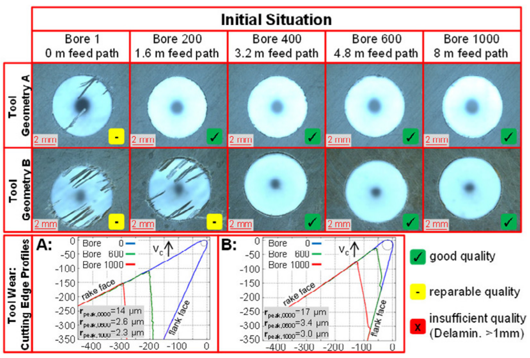


Figure 24: Self-sharpening tools with cutting in CFRP [53]

For geometrically defined cutting edges of even more interest is the possibility to keep the cutting geometry despite of wear attack stable, which means mainly the micro geometry, namely the cutting edge radius. Here the archetype is the beaver tooth as shown in Figure 23. The beaver tooth contrary to technical systems I growing, which means that the worn geometry is replaced. So the material composition must be such, that wear reproduces the cutting geometry of the growing tooth, which is achieved by graded material, sharp inside and soft outside, so that the reset of the surface at the heavily loaded cutting edge is the same as in the less loaded rake and flank faces of the tooth. A similar approach is presented by Henerichs [24], Voss [54] and in [25] for tools for cutting of carbon fibre reinforced plastics (CFRP), which can be adopted for all abrasive material types. The carbon fibres are hard and due to fibre breakage sharp-edged and thus deteriorating cutting edges strongly. On the other hand, cutting, esp. drilling requires that the fibres are neither torn out nor stay uncut, which requires extremely sharp cutting edges, which are exposed and prone to wear. Figure 24 shows the principle, namely concentrating the wear onto the flank face, while the rake face is covered by a hard and thick diamond coating, by this making up a “graded” material. The benefit of this approach can clearly be revealed by drilling experiments, which is insofar of industrial interest as all CFRP parts in the aerospace industry are riveted together. Even after 1000 holes in unidirectional material IMA which means a total hole depth of 8 m the tool is still sharp enough to totally cut the fibres, while in the first 200 holes the bore hole quality measured by uncut fibres in the exit of the drill is insufficient. This can be enhanced by pre-wearing the tool through laser ablation, which serves twofold, reducing the cutting edge radius and weakening the diamond coating on the flank face, which serves again to concentrate the wear there. The advantage of the drilling process is that the actual position in feed direction of the cutting edge is without interest, which means that the reset of the cutting edge is of no relevance. Milling and turning requires accompanying measures, namely a wear compensation with the help of a wear model for the recalculation of the actual cutting edge position in the tool coordinate system and the respective tool corrective movements of the machine axes. And yet another topic needs to be discussed. As can be seen in Figure 24 the contact length of the flank face increases due to the fact, that wear distribution is not optimally realized and the geometrical setback not the same everywhere. This results in excessive growth of the feed forces. Besides the already discussed grading of the material for instance by means of additive manufacturing of the tool body also the geometry of the flank face can be designed such, that the inbuilt vitality reserve of the tool becomes larger, for instance with a stepped flank face.

6. Sensors

6.1. Sensor based Cognition in Machines

The common trait of cognitive and biointelligent systems is their ability to replicate human capabilities, such as perception, reasoning, adaption and evolution. In order to shed light on the different facets of cognition in manufacturing, it is useful to distinguish between cognition on the machine level, referred to as Cognitive Technical Systems (CTS) [66], and cognition on factory level, referred to as Biological Manufacturing Systems (BMS) [52], or Cognitive Factories (CF) [65]. The underlying principle being similar, it does nonetheless make sense to separate these two aspects, as their outcome does differ significantly. The subsequent findings are related to cognition on machine level.

Cognitive Technical Systems (CTS): CTS are characterized by the presence of artificial sensors and actuators, as well as their integration or embedding into physical systems [8,66] as shown in Figure 25. Contrary to conventional technical systems, CTS are able to perceive, learn, plan and reason. A central capability of a cognitive control system is therefore to react autonomously to changing conditions as well as unexpected events [55].

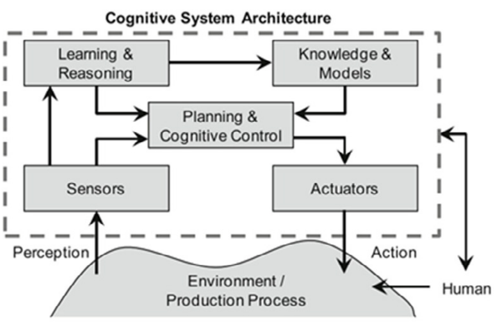


Figure 25: Cognitive Technical System (CTS) Definition as introduced by Zaeh *et al.* [66]

Based on a cognition model fulfilling this criterion, Shea *et al.* [48] demonstrated a framework to implement cognitive capabilities in a milling process for individual parts. The framework considers both machine and factory level aspects. The on-machine aspects are a flexible fixture planning and re-configuration, as well as toolpath planning and evaluation. The publication has an explorative rather than an exploitative character, given that the performance of the system is neither reviewed nor compared to others.

6.2. Sensors in Abundance

Cognition describes the forming of knowledge through experience and thought, for which sensors provide the necessary data acquisition structure. A critical factor for the application of learning approaches is the information content of the data acquired by the system. As knowledge can only be extracted if the necessary information is present in a sufficiently large, comprehensive and minimum-resolution dataset, the appropriate use of sensors is the prerequisite of cognitive systems. Taking the human as the role model for cognitive capabilities, the ubiquitous use and combination of sensors of different natures (optical, acoustic, olfactory, haptic and others) comes to mind. In this fashion, the large array of sensors distributed across common machine tool architectures and connected to the Control Systems seems to correspond to this notion of Sensors in Abundance. However, Gittler *et al.* [20] point out that the availability of data on current-day machine tools is limited in various sights, and that additional sensor structures need to be deployed in order to allow for a more complete range of cognitive and analytical tasks. They propose a data acquisition architecture, in which internal, external and virtualized sensors of machine tools can be merged in order to ensure a thorough availability of data, advancing sensor architectures on machine tools towards the notion of Sensors in Abundance.

6.3. Exploitation of Optics

A particular example of ubiquitous data inflow is the usage of camera systems. The advantage of optics used in mechatronic systems is their ability to capture a large range of characteristics, the alignment of the information scope with the image boundaries, and the affordable and intuitive use in manufacturing environments. Given the common underlying principle of image transformation and feature recognition, which can be deployed from one system to another in cases of transfer learning, it has ever since been at the forefront of learning and cognitive research. Nagato *et al.* [40] proposed the approach of Figure 26 in 2017, in which a camera system identifying accept or reject parts on a manufacturing line is introduced. Failure-detection and recovery techniques are implemented, allowing the camera system to autonomously adapt to both environmental and specification changes without noticeable drops in the recognition rate. Due to modifications in the production environment (replacement or adjustments of components, changing lighting conditions, different camera installation alignments), the recognized images can suddenly differ a lot. In order to overcome this issue, the changing conditions are identified, and the analysis model is continuously updated. For sudden and very harsh changes, the intervention of an expert to requalify the underlying model can be implemented.

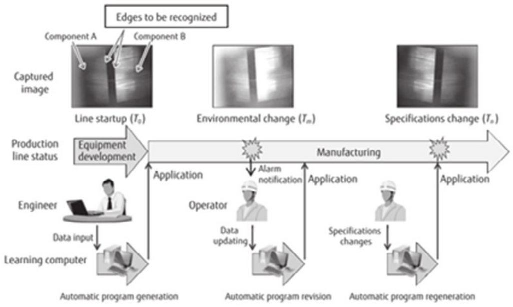


Figure 26: Image Recognition System Architecture, conceived by Nagato *et al.* [40]

This system corresponds to the here within defined notions of Cognitive Technical Systems, learning with structured data, transfer learning, and Self-Organizing Systems. It adopts image recognition capabilities of other algorithms, whilst being trained on the specific job with images of accept and reject parts, to which the outcome is specifically known. Additionally, the system is capable of actively detecting a predefined set of changes, and it reacts autonomously to mitigate the effects of changes on the overall system behavior.

7. Conclusions

Biological systems have some properties making them clearly superior to today's technical systems, which has been shown so far, which makes it desirable to enhance technical systems with beneficial properties of biological systems. This is in the long line of development of production machines a logical consequence. The increased understanding of systems behaviour and from this perpetual optimization has reached a state, where deterministic approaches become extremely complicated or reach their limits. Together with the unprecedented possibilities of data evaluation cognitive systems discussed already long ago become now possible and beneficial. This "biologicalization" of technical systems enables to overcome the vulnerability of highly developed technical systems and increase their robustness against faults as well external as internal disturbances. Especially for production systems that have to master their processes with highest repeatability and quality, such that only very limited group of operators are capable to fulfil this task can greatly profit from cognitive capabilities of biological systems. Releasing the operators from complexity can only be achieved if the production machine deals autonomously with the full complexity of the physics of machine, process and environment, which is only achievable with machine cognition and machine learning approaches. "Intelligence" to the machine necessarily requires to overcome the today's separation between intelligent planning systems and stupid execution systems, where machines without a generalized CAM, like grinding and EDM might become the forerunners of biologicalization. To enhance this development process, a multitude of machines needs to be observed and thus Industrie 4.0 is necessary prerequisite for this approach. As the number of same machines in same operating conditions are sparse, modelling to make data comparable, to transform them to data for a master system plays a significant role. In every respect, it is worthwhile to systematically imagine which properties of biological systems are worth to be considered in production machinery, generating not only a new type of machine, but also a new type of machining processes and factory organization. An estimation of time scales and industrial readiness of different biologicalization approaches is given in Figure 27. An excellent overview on aspects of biological transformation of production is given in [9].

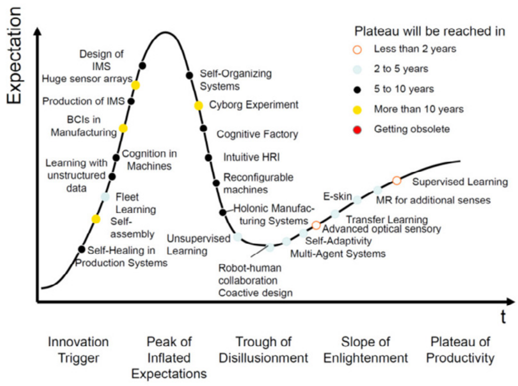


Figure 27: Aspects of biologicalization illustrated within the Gartner Hype cycle.

Acknowledgements

The authors are grateful for information provided by P. Blaser and T. Haas and the financial support of the Commission for Technology and Innovation CTI, Switzerland as well as for the support of MTTRF, San Francisco.

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