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TECHNICAL MONITORING AND DIAGNOSTICS: INDISPENSABLE ELEMENT OF INTELLIGENT MANUFACTURING SYSTEMS

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Abstract: The application of pattern recognition techniques, expert systems, artificial neural networks, fuzzy systems and nowadays hybrid artificial intelligence techniques in manufacturing can be regarded as consecutive elements of a process started two decades ago. The paper outlines the most important steps of this process. Agent-based systems are highlighted as promising tools for managing complexity, changes and disturbances in production. Further integration of approaches is predicted.

Keywords: Technical monitoring and diagnostics, artificial intelligence, machine learning, intelligent manufacturing systems.

1. INTRODUCTION

Manufacturing systems of our days work in a fast *changing environment* full of *uncertainties*. Increasing *complexity* is another feature showing up in production processes and systems, furthermore, in enterprise structures as well [1]. One of the recent areas of research is related to the *globalization* of production. *Production networks (PNs)* are formed from independent companies collaborating by shared information, skills, resources, driven by the common goal of exploiting market opportunities.

The concept of the *digital enterprise* [2], i.e., the mapping of the key processes of an enterprise to digital structures by means of information and communication technologies (ICT) gives a unique way of managing the above problems. By using recent advances of ICT, theoretically, all the important production-related information is available and manageable in a controlled, user-dependent way [3].

However, the management, the optimal or near to optimal exploitation of this huge amount of information cannot be imagined without the effective application of the methods and tools of *artificial intelligence (AI)*, sometimes, more specifically, *machine learning* (ML) techniques [4].

1.1. The Manufuture Initiative

On December 1-2, 2003 - upon the initiation of F. Jovane [5], and after an appropriate preparatory work of an Expert Group - the conference Manu*future* was held in Milan, Italy, with the goal of calling the attention of the main stakeholders on the importance of manufacturing, the "*general transformation of all resources to meet human needs*" in the society. In the accompanying Working Document [6], five driving forces were identified for Manu*future*:

- *Increased research and technological development* with longer term research-industry relationships and clearer support to industrial research.
- *International cooperation in manufacturing research*.
- *The key role of education and training* (attractiveness for the young, multi-disciplinarity, education-research-innovation, "training factories".
- *Stimulating operating environment for industrial innovation* (innovating SMEs, intellectual property rights, Euro-patent, etc.).
- *Increased competitiveness of European research* (new funding instruments, increased networking to reduce fragmentation, long-term vision).

Four main directions were further emphasized at the Manu*future* Workshop, July 1, 2004, Dortmund, Germany: *adaptive manufacturing, digital manufacturing, knowledge-based manufacturing, networked manufacturing.*

The above areas were also outlined at the Manu*future* 2004 Conference, Enschede, The Netherlands, December 6-7, 2004 (http://www.manufuture.utwente.nl/) and in the material Manu*future*: A Vision for 2020, Assuring the Future of Manufacturing in Europe [7].

However, it must be pointed out that the four important areas emphasized above represent overlapping domains and can be considered in a holistic way only. At least two important requirements, i.e., the *real-timeness* and *cooperativeness* of the whole system, have to be added as issues of high and increasing importance.

The first one refers to the ability of recognising and acting on internal and external changes and disturbances within the time frameworks required by the given level of the manufacturing-production hierarchy. Obviously, on the one hand, technical monitoring and diagnostics (TMD) is an indispensable in the manufacturing structures with the abilities required above, and, on the other, the techniques developed and applied within TMD, can be applied in other kinds of change / situation recognition and management, as well. The second issue underlines the fact that the complex production structures – from machine tools, robots, etc. to production networks, including human beings involved – are more and more considered and built up as autonomous, but cooperative entities.

The detection of changes and uncertainties is one of the most important requirements of today's manufacturing. In the paper – partly based on [8] - pattern recognition (PR) techniques, expert systems (ESs), artificial neural networks (ANNs), fuzzy systems (FSs) and hybrid AI techniques in manufacturing are outlined as consecutive elements of a process started two decades ago. Further integration of approaches - also with agent-based systems - is predicted.

The also illustrates how the above R&D directions outlined within the Manu*future* initiative are manifested in two (one just completed, one just started) large-scale national R&D projects, i.e., one on *Digital Enterprises, Production Networks*, the other on *Real-time, Cooperative Enterprises*, by illustrating the results achieved and future research directions, as well.

2. MANAGING UNCERTAINTIES AND CHANGES IN PROCESS / MACHINE LEVEL

The PR - ANNs - hybrid AI systems evolution in applications can be found in this section where the overlapping fields of tool condition monitoring, process modelling and adaptive control issues will be treated. Special emphasis is laid on learning abilities, admitting that learning cannot be treated separately from the other important issues (self-calibration, signal processing, decision making, fusion ability, etc., [9]).

2.1. Tool condition monitoring (TCM)

The application of numerical PR techniques for monitoring purposes started with linear decision functions trained iteratively [10], [11]. *Fuzzy PR* techniques proved to be efficient tools for dealing with the uncertain nature of cutting processes [12]. A number of *multipurpose monitoring systems* were developed on the basis of PR, multisensor integration and parallel processing through multiprocessor systems [13], [14], [15].

PR is the field, where ANNs seem to have the most potential benefits for practical applications. Taking into account other favourable features of neural networks (e.g. parallelism, robustness and compactness), it was expected that this technique can be advantageously used in different fields of manufacturing.

Dornfeld applies ANNs for TCM [16]. The applicability of ANNs for multisensor integration (acoustic emission (AE) and cutting force) was demonstrated. The comparison of results gained by linear classifiers and ANNs' trained by the back propagation (BP) technique, outlined their better noise suppression and classification abilities.

One of the main - but often neglected - problems in monitoring of machining processes is *how to treat the varying process parameters*. Possibilities for incorporating process parameter information into the learning and classification phases were demonstrated in [17]:

- networks trained under constant process parameters,
- networks trained under varying process parameters,
- networks incorporating process parameters as inputs.

Combined structure and parameter learning technique through a neuro-fuzzy (NF) system for the classification of the wear states of milling tools in four categories was described in [18]. A four-step learning algorithm integrating self-organised clustering, competitive learning, and supervised BP learning techniques was applied for determining the fuzzy rules and the parameters of the membership functions. The *NF technique* with structure and parameter learning showed superior performance to the BP solution and previous investigations with a commercial NF system. Further improvements have been reached by using genetic algorithms for rule set generation [19].

2.2. Process modelling

Reliable process models are extremely important in different fields of computer integrated manufacturing, such as design, optimisation, control and simulation of processes and design of equipment [20]. Difficulties in modelling manufacturing processes are manifold: the great number of different machining operations, multidimensional, nonlinear, stochastic nature of machining, partially understood relations between parameters, lack of reliable data, etc. In the CIRP survey on developments and trends in control and monitoring of machining processes, the necessity of sensor integration, sophisticated models, multimodel systems and learning ability was outlined [20].

ANNs as learning structures for the lower level of an intelligent controller were suggested in [21]. A *learning process* enables the controller to understand how input variables (such as feed rate, depth of cut, and cutting velocity) affect output variables (such as cutting force, power, temperature and workpiece surface finish) in the case of a turning operation.

The decision-making approach of [22] incorporates several process models that correlate process state variables such as surface roughness or chip merit mark to process parameters such as feed rate, cutting speed and tool rake angle. In [17] inverse models of the milling process, i.e. separate models for three process parameters (axial depth of cut, cutting speed, and tooth feed) were generated always using the other two process parameters and force and vibration features as networks' inputs.

In [23] a novel approach for generating multipurpose models of machining operations combining machine learning and search techniques is described. Simulated annealing search is used for finding the unknown parameters of the multipurpose model in certain applications including modelling of process chains.

2.3. Adaptive Control (AC)

The above described investigations for determining suitable process models for machining operations aimed at realising powerful adaptive control schemes.

The task to be fulfilled can be formulated as follows. There exist some limitations on input variables (e.g. machine limitations), some output variables are to be kept sufficiently close to the desired values and others can have upper limits (e.g. vibration). The algorithm suggested in [21] is based on an augmented Lagrangian method to minimise a properly selected combined performance index, which takes into consideration the above requirements.

Two hybrid AI systems for control and monitoring of manufacturing processes on different hardware and software bases were described in [24]. In these hybrid systems, networks outputs are conveyed to an expert system that provides process control information. On the base of accumulated knowledge the hybrid systems influence the functioning of the subsymbolic levels, generate optimal process parameters and inform the user about the actual state of the process.

In the *HYBEXP* system [25], an artificial neural network simulator called *NEURECA* constitutes the *lower, subsymbolic level*. The *higher, symbolic level* is based on the commercially available AI expert system shell. The results of the lower level are conveyed to the symbolic part, where using additional stored knowledge (e.g. the type and number of cutting tools available, actual cutting parameters, the parts to be machined, etc.) different decisions can be made. *HYBEXP* can initiate e.g. machine stop, tool change, modification of cutting parameters (AC control) or change of parts to be machined. *HYBEXP* can work also as a *decision support system*.

2.4. Modelling and management of process chains

In order to realise adaptive control of a *production chain*, models have to be ordered to every stage of the production and connected by their input-output parameters. In [26] a software package ProcessManager is described, which supports the modelling and adaptive control of processes and process chains as well. It incorporates:

- definition of the elements of the chain,
- determination of the process models in a hybrid way, by integrating analytical equations, expert knowledge and example-based learning,
- connection of the single models into a process chain by coupling input-output model parameters not limited to models of successive processes in the chain,
- definition of eligible intervals or limits for the process parameters and monitoring indices,
- definition of a cost function to be optimised, etc.

3. MANAGEMENT OF COMPLEXITY, CHANGES AND DISTURBANCES IN SYSTEM LEVEL

In today's manufacturing systems, difficulties arise from unexpected tasks and events, non-linearities, and a multitude of interactions while attempting to control various activities in dynamic shop floors. *Complexity* and *uncertainty* seriously limit the effectiveness of conventional control and *(off-line, predictive) scheduling* approaches [27].

The performance of manufacturing companies ultimately hinges on their ability to rapidly adapt their production to current internal and external circumstances. Two main kinds of approaches to dealing with the enumerated problems are: to enhance the reactivity of traditionally structured (mostly hierarchical) systems by sophisticated new control techniques, and to construct decentralised, distributed systems. Another - also overlapping - way of dealing with changes and disturbances is to develop *adaptive systems*, which are able to learn from past history.

A survey of reactive scheduling approaches can be found in a recently published book chapter [28]. Here we concentrate on distributed, agent-based approaches.

3.1. Multi-agent manufacturing control

In order to overcome inflexibility, rigidity associated with the traditional hierarchical control of manufacturing systems, the heterarchical approach has been proposed. This approach represents a highly distributed form of control, implemented by a system of independent co-operating processes or agents without centralised or explicit direct control.

Agent technology [29] is considered an important approach for developing distributed manufacturing systems [30]. Holonic manufacturing systems (HMSs) consist of autonomous, intelligent, flexible, distributed, co-operative agents or holons. The PROSA reference architecture for HMSs [31] identifies three types of basic holons, i.e., resource, product, and order holons. Staff holons are also foreseen to assist the basic holons in performing their work. Other authors refer only to two types of basic building blocks, e.g., order and machine agents, job and resource agents, or order and machine (resource) holons [32]. One of the most promising features of the holonic approach is that it represents a transition between fully hierarchical and heterarchical systems [33].

3.2. Market-based resource allocation

Co-operation and conflict resolution are the main issues in agent-based systems. Negotiation-based algorithms are mostly used where schedule generation is a recursive, iterative process with announce-bid-award cycles based on market mechanisms [34].

In the simulation described in [35] the objective in the bid evaluation procedure can be the minimisation of production costs, job tardiness, makespan or weighted combination of the above or similar factors. The weights of the objective functions can be dynamically adjusted on the basis of the system state and external conditions resulting in different control strategies and system performance.

Naturally, there exist different variations of the above simplified procedure. Order (or part) driven and resource (machine, cell) driven techniques can be distinguished based on who makes the announcements. More advanced systems support also look ahead scheduling with a longer, sometimes varying horizon [8].

3.3. Stigmergy-based co-ordination and control

A relative novel approach for co-ordination in multi-agent systems is stigmergy which belongs to mechanisms which mimic animal-animal interactions [36]. Stigmergy is an indirect co-ordination tool within an insect society where parts of global information is made available locally by pheromones, e.g., in the case of ant colonies. This way, individual ants are not exposed to the complexity and dynamics of the situation, and the communication burden in the computer realisation is significantly lower, compared to market-based solutions.

As to the realisation of stigmergy-based systems, virtual ants can be realised by mobile software agents or even message-based realisation can be conceived, as well. It may not be stated that market- and stigmergy-based approaches represent two totally different ways of multi-agent co-ordination and control, they can be nicely combined in complex societies.

3.4. Adaptation and learning in multi-agent production control

Learning and other forms of adaptation are essential in multi-agent systems [4], [32]and can be categorised as:

- Centralised learning (or isolated learning) refers to learning approaches which are entirely executed by single agents, completely independent and exclude the interaction with other agents.
- Decentralised learning (or interactive learning) involves several agents which require a joint and co-ordinated interaction among them.

Adaptive market-based resource allocation

The adaptation procedure described in [32] is a centralised approach in which each resource agent locally adapts its behaviour to achieve a more profitable position in the agent society. The feedbacks are represented by changes in local utilisation parameters and bid awarding and/or rejection reactions issued by the order agent. Each resource agent incorporates a rule base by which it can locally decide on the cost factor to be applied for an announced task. The preconditions of these rules are the utilisation of the resource and the ratio between the won and lost bids which are stored locally for each agent in the table of machine abilities and history.

Simulation results demonstrate that the major advantage of the proposed solution is a more equilibrated usage of resources. Moreover, several performance measures such as maximum tardiness and makespan proved to be better with cost factor adaptation.

Neurodynamic programming and simulated annealing in multi-agent-based scheduling

The main aim of the work reported on in [37] was to decrease the cost of computing in scheduling by

- *de*creasing the communication load of the order agents by partly assigning their tasks to the resource agents, in this way, further parallelising the process of scheduling and resource allocation,
- decreasing the number of mobile agents (virtual ants) to be sent to other resources,
- improving agents' actions in given situations/states by artificial neural network (ANN) based learning,
- estimating the remaining processing times of jobs together with their most appropriate routes through the resources by reinforcement learning,
- balancing between exploration and exploitation in the system by using simulated annealing; and, as a result, of the above sub-goals, to
- lay down an approach for multi-agent control, which can manage internal and external changes and disturbances, offers any-time solutions which can be improved if longer time is available, and finally, is feasible from computational point of view, as well.

The system resulted represents a three-level decentralised learning scheme combining neurodynamic programming (reinforcement learning + neural network) and simulated annealing [37].

4. CONCEPTS AND MAIN RESULTS OF HUNGARIAN R&D PROJECTS TOWARDS MANU*FUTURE*

4.1. Digital enterprises, production networks

The results presented here have been conceived and developed in the framework of a project run in Hungary on Digital Enterprises, Production Networks [3]. The main intention of the partners was to develop solutions which are based on novel fundamental research, but, at the same time, applicable in the industry. The integrative endeavour of the partners was to make all the production-related information available and manageable in a controlled, user-dependent way by the efficient use of information and communication technologies, i.e., to develop decision support systems, in order to help enterprises to cope with the problems of uncertainty and complexity, increase their efficiency, join in production networks and to improve the scope and quality of their customer relationship management.

The partners wanted to make progress in the following – partly overlapping – directions, project clusters:

- *management and scheduling of large-scale projects,*
- *tele-presence and interactive multimedia,*
- *monitoring of complex production structures* [38].

4.2. Concept of VITAL, the national project on real-time, cooperative enterprises

One of the most important trends in manufacturing is manifested in the paradigm of *customised mass production*, which means difficult to accomplish the task of producing *customised products at a price near to the level in mass production*.

The national research project *VITAL: Real-time Cooperative Enterprises* incorporating a big multinational enterprise, its three suppliers, two Hungarian universities, Fraunhofer IPA, Stuttgart, and SZTAKI as the project leader, intends to develop IT-solutions for enterprises producing mass customized products and working in networks. In addition to customised mass production, issues are to be handled, like

- globalisation, increasing competition, frequently changing, uncertain environment,
- growing complexity of production processes, manufacturing systems and enterprise structures,
- autonomous, partly competing, partly cooperating production structures.

The goal of the project is to research and develop new methods for the real-time management of complex technical and economic systems that work in changing, uncertain environments. Since the methods come from various, novel areas of informatics, operational research and knowledge-based systems, their integration will balance the aspects of optimisation, autonomy, and cooperation.

Fig. 1 summarizes the main endeavours: the research and development of solutions from the level of production networks through single enterprises to production lines, which can ensure the optimal / near to optimal behaviour of the whole system, and moreover, in a *real-time* fashion required by the given level of production.

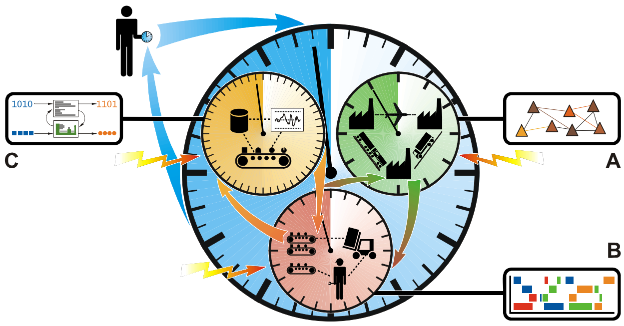

Fig. 1. General concept of the VITAL project.

The orders are to be fulfilled in good quality, on the agreed price and *on time*. The customers do not necessarily realize that they usually face a conglomerate of firms, i.e., production networks. The importance of the *time* is illustrated by the watches in the figure, which incorporates the different levels (network, enterprise, production line) of the production expected to react on the external and internal changes and disturbances (indicated by thunderbolts) with a *reaction time* characterising the level in question.

The problems to be solved are as follows (referring to the notations of Fig. 1):

- *integrated production planning and scheduling (B),*
- *real-time production control (C),*
- *management of distributed, cooperative systems (A).*

The reason for the above sequence is that the high-level resource-management and scheduling of enterprises can give the basis, on the one hand, for the reliable, optimal or near to optimal management of supply chains and production networks, and, on the other, for handling changes and disturbances in shop floors or production lines.

5. CONCLUSIONS

Learning process models, *cause-effect relations*, automatically *recognising different process changes* and *degradation* and *intervening* in the process in order to ensure economic and safe processes and product qualities are sophisticated approaches with high potential. They are the subjects of intensive research and development work worldwide. The complexity of the problem and the associated uncertainties necessitate the application of *learning techniques* to get closer to the realisation of *intelligent manufacturing systems*. Further integration of different techniques, such as AI, machine learning and agent-based approaches can be predicted.

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