

AI AND MACHINE LEARNING TECHNIQUES FOR MANAGING COMPLEXITY, CHANGES AND UNCERTAINTIES IN MANUFACTURING

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Abstract: The application of pattern recognition (PR) techniques, expert systems (ESs), artificial neural networks (ANNs), fuzzy systems (FSs) and nowadays hybrid artificial intelligence (AI) techniques in manufacturing can be regarded as consecutive elements of a process started two decades ago. On the one hand, the paper outlines the most important steps of this process and introduces some new results with special emphasis on hybrid AI and multistrategy machine learning (ML) approaches. On the other hand, agent-based (holonic) systems are highlighted as promising tools for managing complexity, changes and disturbances in production systems. Further integration of approaches is predicted. *Copyright © 2002 IFAC*

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1. INTRODUCTION

Growing complexity is one of the most significant characteristics of today's manufacturing, which is manifested not only in manufacturing systems, but also the products to be manufactured, in the processes, and the company structures (Wiendahl and Scholtissek, 1994). The systems operate in a *changing environment rife with uncertainty*.

The term of *Intelligent Manufacturing Systems (IMs)* can be attributed to a tentative forecast of Hatvany and Nemes (1978). In another landmark paper of Hatvany in 1983, IMs were outlined as the next generation of manufacturing systems that - utilising the results of the AI research - were expected to solve, within certain limits, unprecedented, unforeseen problems on the basis of even incomplete and imprecise information (Hatvany, 1983).

The most frequently cited definition of learning comes from Simon (Simon, 1983): "Learning denotes changes in the system that is adaptive in the sense that they enable the system to do the same task or tasks drawn from the same population more effectively the next time". With respect to advanced engineering automation, as stated in (Lu, 1990), "we need new computer technologies that cannot only generate, record, and retrieve information, but also digest and synthesise *information into knowledge* and represent this knowledge properly to support decision making". It can be emphasised that intelligence is strongly connected with learning, and learning ability must be an indispensable feature of IMs (Monostori, *et al.*, 1996).

The structure of the paper is as follows. Section 2 gives a short survey of AI and ML techniques available. Approaches to handling changes and uncertainties in the process / machine level are treated in Section 3. System level issues are

addressed in Section 4, while Section 5 attempts to draw some conclusions and to highlight some future research directions.

2. AI AND ML TECHNIQUES FOR INTELLIGENT MACHINES AND SYSTEMS

Over the past decades, the field of artificial intelligence has made great progress toward computerising human reasoning. *Symbolic approaches* are based on the *hypothesis of symbolic representation* - the idea that perception and cognitive processes can be modelled as acquiring, manipulating, associating, and modifying symbolic representations. *Expert systems* represent the earliest and most established type of intelligent systems attempting to embody the “knowledge” of a human expert in a computer program. Knowledge representation in these systems proceeds symbolically in the form of *production rules*, *frames* or *semantic networks*.

A different approach to intelligent systems involves constructing computers with architectures and processing capabilities that mimic the processing characteristics of the nervous system. The technology that attempts to achieve these results is called *neural computing* or *artificial neural networks*. These *subsymbiotic methods* work with *numeric values* and seem to be more appropriate for dealing with perception tasks and perhaps even with tasks that call for combined perception and cognition.

Investigations confirmed that - similarly to our present conception of biological structures - adaptive ANN techniques seem to be a viable solution for the lower level of intelligent, hierarchical control and monitoring systems where abilities for *real-time functioning*, *uncertainty handling*, *sensor integration*, and *learning* are essential features. Since the higher levels of the control and monitoring hierarchy require mostly symbolic knowledge representation and processing, the *integration of symbolic and subsymbiotic methods* is straightforward (Monostori and Barschdorff, 1992).

Several techniques for integrating expert systems and neural networks have emerged over the past few years spreading from *stand-alone* models, through *transformational*, *loosely* and *tightly coupled* models to *fully-integrated expert system/neural network models* (Kandel and Langholz, 1992). The integration of neural and fuzzy techniques, which can be considered as a “full integration”, is an approach of high importance.

Over the past years significant research efforts have been devoted to the development and use of *Distributed Artificial Intelligence (DAI)* techniques (e.g. Bond and Gasser, 1988). An *agent* is a real or virtual entity able to act on itself and on the surrounding world, generally populated by other agents. Its behaviour is based on its observations, knowledge and interactions with the world of other agents. An agent has several important features. It has capabilities of perception and a partial representation of the environment, can communicate with other agents, can reproduce child agents, and has own objectives and an autonomous behaviour (Koussis, *et al.*, 1997). A *multi-agent system (MAS)* is an artificial system composed of a population of autonomous agents, which co-operate with each other to reach common goals, while simultaneously pursuing individual objectives (Koussis, *et al.*, 1997).

A *learning agent* (Fig. 1) can be outlined as one having several modules: first, it is the *acting module*, which takes percepts both of the external world and its own state and selects the external actions of the agent. The *learning module* improves the actions of the acting module. The learning process could be assisted by a *critic module*, which applies external performance standards, and the *problem generator module*, which suggests deliberate *exploratory actions*, so that the agent's view of the world should become more and more appropriate. (As it will be seen later, in most applications only some of these modules have been developed.)

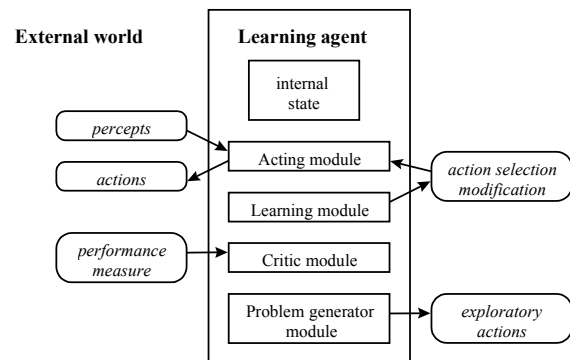


Fig. 1. General model of a learning agent and its interactions with the external world

Learning processes could be classified by the available feedback. These are

- *supervised* learning: the correct response is provided by a teacher,
- *reinforcement* learning: less feedback is given, since not the proper action, but only an evaluation of the chosen action is given by the teacher,
- *unsupervised* learning: no evaluation of the action is provided, since there is no teacher.

While in the first two methods the *teach-in* and *application* phases can be clearly distinguished even when they occur in cycles, in unsupervised learning usually there is no distinct, predefined teach-in phase; in most cases the learning system itself should give a signal of being fairly trained.

While various kinds of simple learning methods work with *examples* only, the more powerful learning systems make use of some *background knowledge* of the world.

Most research in *machine learning* has been concerned with methods that employ a single learning strategy, that is, with *monostrategy* methods. With the growing understanding of the capabilities and limitations of monostrategy methods, there has been an increasing interest in *multistrategy* systems that integrate multiple inference types and/or computational mechanisms in one learning system. Such systems are expected to learn from wider scope of input, and be applied to a wider range of problems than monostrategy methods (Monostori and Barschdorff, 1992).

3. MANAGING UNCERTAINTIES AND CHANGES IN PROCESS / MACHINE LEVEL

The pattern recognition - artificial neural networks - 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. (Byrne, *et al.*, 1995)).

3.1. Tool Condition Monitoring (TCM)

The application of numerical PR techniques for monitoring purposes started with linear decision functions trained iteratively (Sata, *et al.*, 1973; Dornfeld and Bollinger, 1977; Zhang, *et al.*, 1982). *Fuzzy PR* techniques proved to be efficient tools for dealing with the uncertain nature of cutting processes (Monostori, *et al.*, 1996). A number of *multipurpose monitoring systems* were developed on the basis of PR, multisensor integration and parallel processing through multiprocessor systems (Weck, *et al.*, 1984; Monostori, 1986).

Dornfeld applies ANNs for TCM (Dornfeld, 1990). 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 the better noise suppression and classification abilities of neural networks.

One of the main - but often neglected - problems in monitoring of machining processes is *how to treat the varying process parameters*. Some possibilities for incorporating process parameter information into the learning and classification phases were demonstrated in (Monostori, 1993):

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

Comparing the different approaches, the best generalisation ability (networks' performance for patterns generated under cutting conditions outside the region considered during the training phase) was achieved with the latter variant, i.e. the networks were able to filter out the disturbing effects of the varying process parameters, and to generalise.

Due to the numeric, real-time nature of TCM, comparing with connectionist approaches, relatively few reports are available regarding the application symbolic learning techniques in this field. In (Junkar, *et al.*, 1991), the identification of the plunge grinding by decision tree generation using vibration signals generated by the grinding wheel was described.

The existence of low dimensional *chaos* in turning was proved, and a unified approach for tool condition monitoring using a combination of wavelets and fractal dimensions was developed in (Bukkapatnam, *et al.*, 1995).

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 (Monostori and Egresits, 1997). A four-step learning algorithm integrating self-organized clustering, competitive learning, and supervised BP learning techniques was applied for determining the fuzzy rules and the parameters of the membership (MBF) functions.

As an example (Fig. 2), 14 rules have been automatically selected from the possible 1152 ones during the competitive learning phase in a *self-organising* way. The mean values and variances of bell shaped MBFs were adjusted to reach a kind of optimum regarding the network error for training patterns (Monostori and Egresits, 1997). 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 (Egresits, *et al.*, 1998).

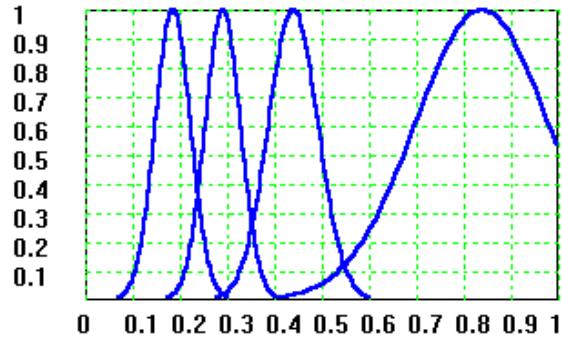
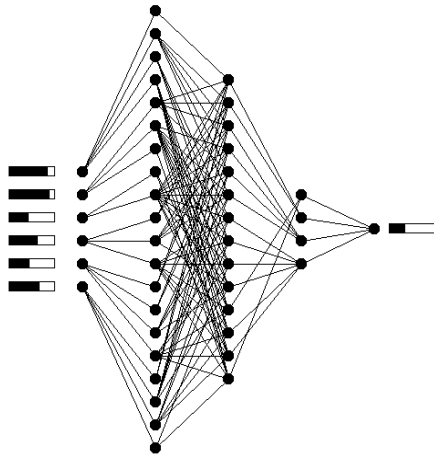


Fig. 2. NF structure for the four-class problem, after learning, with normalised inputs and output and the learnt membership functions for one of the input variables

3.2. 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 (Merchant, 1998; Tönshoff, *et al.*, 1988). Difficulties in modelling manufacturing processes are manifold: the great number of different machining operations, multidimensional, non-linear, 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 (Tönshoff, *et al.*, 1988).

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.

ANNs as learning structures for the lower level of an intelligent controller were suggested in (Rangwala and Dornfeld, 1989). A *learning process* (Fig. 3) enables the controller to understand how input variables (such as feed rate (f), depth of cut (d), and cutting velocity (v)) affect output variables (such as cutting force (F), power(P), temperature(T) and workpiece surface finish (R)) in the case of a turning operation.

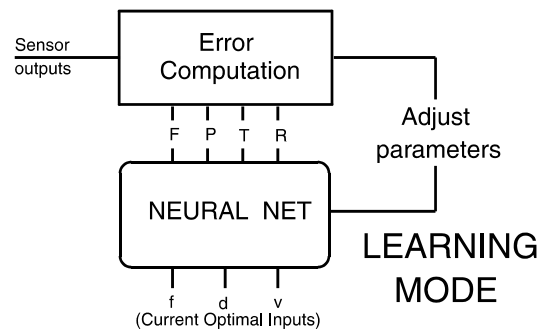


Fig. 3. Learning of process models in machining

The decision-making approach of (Chryssolouris and Guillot, 1988) 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 (Monostori, 1993) inverse models of the milling

Analytical models (e.g. for forces or wear occurring in profile grinding) are available and can be adapted to different quantities by using learning strategies. These analytical models can be combined by simulation techniques, e.g. by FEM simulation to estimate the thermoelastic behaviour of the workpiece. ANNs due to their high adaptivity and non-linearity can be advantageously used also here (Fig. 4, Westkämper, *et al.*, 1995). The combination of multisensor integration, propound signal processing, adaptive models, process simulation can lead to the adaptive control of quality.

In (Monostori and Viharos, 1999) 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.

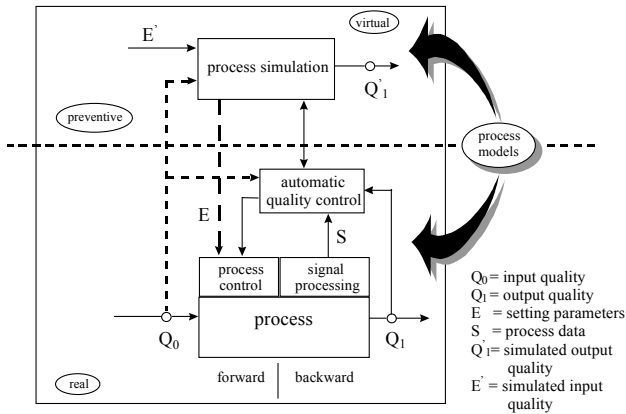


Fig. 4. Optimisation and preventive quality assurance for manufacturing processes

3.3. 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 (Fig. 5). 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 (Rangwala and Dornfeld, 1989) is based on an augmented Lagrangian method to minimise a properly selected combined performance index, which takes into consideration the above requirements. Their attractive algorithm, which implies forward and BP, has resulted in good performance using simulated data.

As further improvement to this “batch mode” technique (where the learning and synthesis are done separately) a so-called incremental approach was introduced, where the learning and synthesis phases proceed simultaneously. However, during this incremental operation only a part of the possible input space is scanned, mostly the region near to the operating point. Tested with values further from this region, the network showed poor generalisation properties (Rangwala and Dornfeld, 1989).

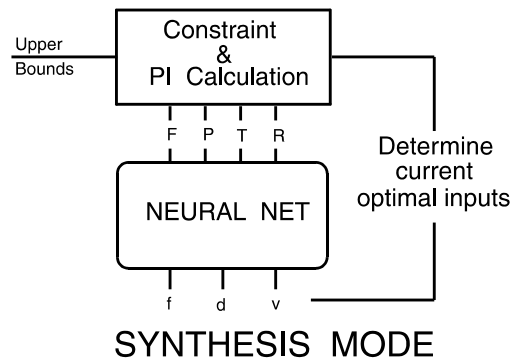


Fig. 5. Synthesis phase of the neural network based adaptive control

One of the most well known models for intelligent machining was introduced in (Chryssolouris, *et al.*, 1987). The control strategy is based on the simultaneous measurement and processing of different signals (force, temperature, acoustic emission). These signals are fed into independent process models. The essential element of this structure is the synthesis of the different sensor information.

Two hybrid AI systems for control and monitoring of manufacturing processes on different hardware and software bases were described in (Barschdorff, *et al.*, 1997). 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 (Monostori, 1995), an artificial neural network simulator called *NEURECA* constitutes the *lower, subsymbolic level* (A in Fig. 6). The *higher, symbolic level* is based on the commercially available *GoldWorks III* expert system shell (B).

Both the symbolic and neural subsystems are connected to the machine tool (the machine tool controller is incorporated). The symbolic part forwards (II) process parameter information (feed rate, depth of cut, cutting speed) to the machine tool (C). The generated indirect signals (e.g. force components, vibration) are measured and conveyed (III) to the subsymbolic part (A) of the hybrid system.

In the figure the machine tool is substituted by a *simulator* of the manufacturing process (called *SIMURECA*, a version of *NEURECA*), enlightening the test and demonstration of the system. On the base of accumulated knowledge and actual process

parameters (cutting speed, feed rate, depth of cut), *SIMURECA* estimates the selected features of the force and vibration signals. These features are

forwarded to the *NEURECA* subsystem, which fulfils the estimation or classification assignment.

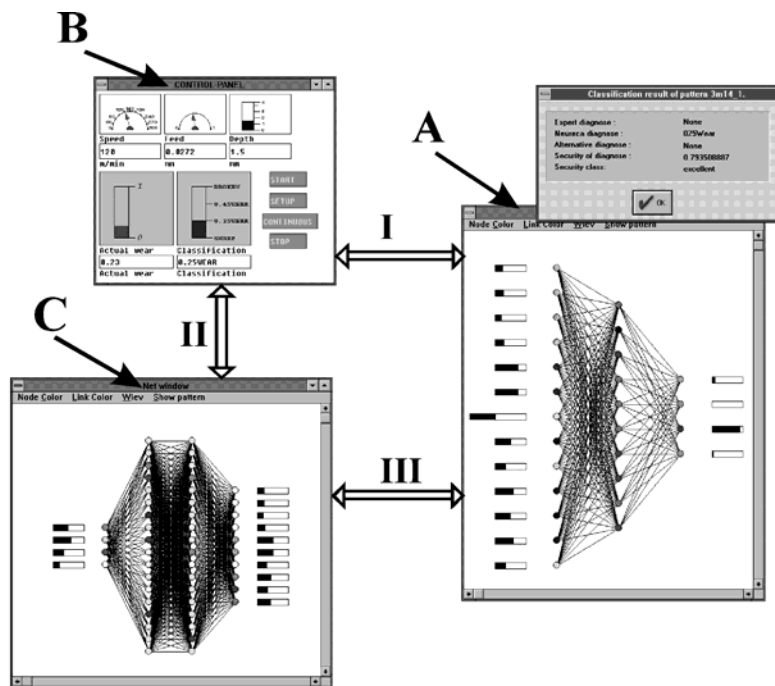


Fig. 6. Components of the *HYBEXP* hierarchically structured hybrid AI system

According to previous investigations (Monostori, 1993), reliable ANN models for classification of cutting tools or for tool wear estimation using indirect signals can only be constructed if they handle process parameter (e.g. cutting speed, feed rate, depth of cut) information. Therefore, the inputs of ANN models used in *HYBEXP* additionally incorporate cutting parameters to indirect signal features. Models for both classification and estimation can be used.

In both cases the results are conveyed to the hybrid 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*.

3.4. Modelling and Management of Process Chains

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 (Monostori and Viharos, 1999) a software package *ProcessManager* is described, which supports the modelling and adaptive control of processes and process chains as well. It incorporates (Fig. 7):

- 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.

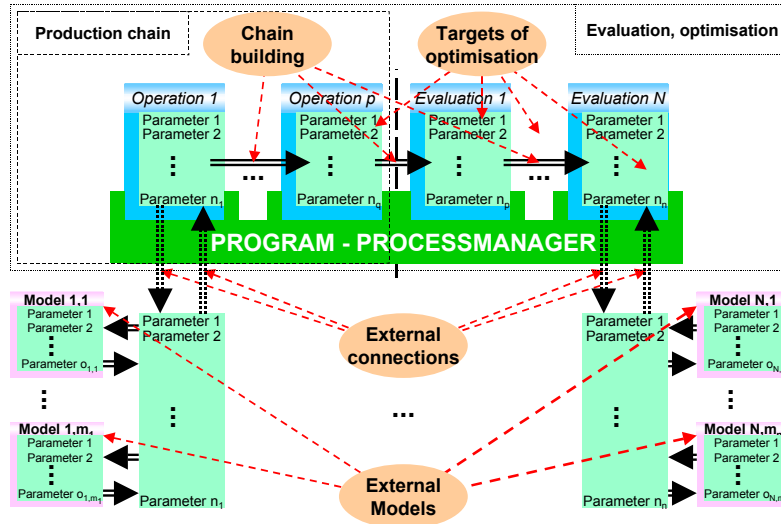


Fig. 7. Hybrid modelling and optimisation of process chains by ProcessManager

4. INTELLIGENT TECHNIQUES FOR 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.

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 (Szelke and Monostori, 1999). Here we concentrate on distributed, agent-based approaches.

4.1. Holonic Manufacturing Systems (HMSs)

Holonic systems, as one of the new paradigms of manufacturing, consist of autonomous, intelligent, flexible, distributed, co-operative agents or *holons* (Valckenaers, et al., 1994).

Three types of basic holons, namely *resource holons*, *product holons* and *order holons*, together with the main information flows between them are defined in (Van Brussel, et al., 1998). These basic entities are structured by using object-oriented concepts such as *aggregation* and *specialisation*. *Staff holons* are also foreseen to assist the basic holons in performing their work. The same paper gives a *reference architecture* for holonic manufacturing systems (Van Brussel, et al., 1998). Other authors refer only to two types of basic building blocks, e.g. order and machine agents in, job and resource agents, or order and machine (resource) holons (Monostori, et al., 1998). A common feature of these approaches is that the functions of the order and product holons are somehow integrated in one basic type.

Hierarchical, heterarchical and holonic control structures for an assembly cell are compared in (Valckenaers, et al., 1994). Holonic systems were found to deliver better performance in a wider range of situations than their more conventional counterparts. One of the most promising feature of the holonic approach is that it represents a transition between fully hierarchical and heterarchical systems (Valckenaers, et al., 1994; Bongaerts, et al. 2000).

The industrial acceptance of holonics, however, is relatively low among others things by reasons of

- the relative *crudeness* of the agent theory and its manufacturing applications,
- the *insufficient communication and decision making capabilities* of present numerical controls,
- the *high investment costs* of a production system working according to the agent principles,

- the seemingly insurmountable difficulties in their *stepwise integration* into existing production systems (Kádár and Monostori, 1998).

Several approaches are introduced and treated in (Kádár and Monostori, 1998) to overcome the above difficulties. Here, approaches are considered where simulation is a key issue.

4.2. Development of Agent-based Architectures by Simulation

There are a number of open questions in holonics (Kádár, *et al.*, 1998), which can be answered by extensive simulation only. The object-oriented simulation framework for the development and evaluation of distributed manufacturing architectures described in (Kádár, *et al.*, 1998) provides a root model that represents a plant and can contain different agents. The object library incorporates two main agent types: resource agent and order agent (Fig. 8).

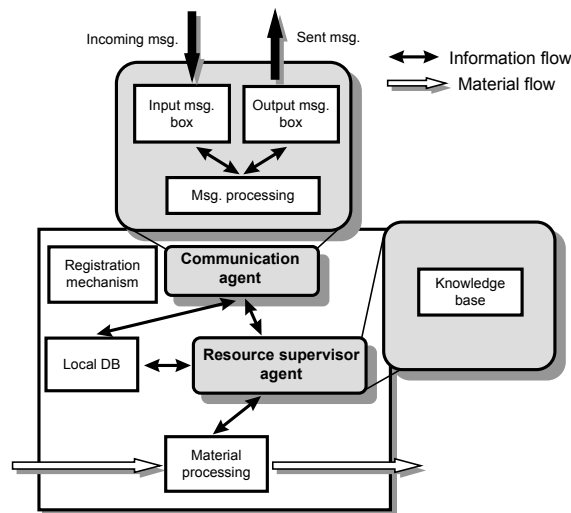


Fig. 8. Structure of a resource agent

A plant in the model will contain only one order agent, which is responsible for order processing, job announcements and job dispatching between different resources or groups. A model may incorporate several resource agents, which can be initialised during construction (giving the name of the resource, process-capabilities of the resource, etc.). Only one information provider, i.e. the registration book, is treated centrally in the system.

The simulation framework is intensively used for research purposes. By its aid, a new approach, which breaks with the decision myopia, a common drawback of distributed approaches, is described in (Monostori, *et al.*, 1998).

4.3. Holonic Control of Traditional Systems by Using Simulation

In (Kádár and Monostori, 1998), a novel approach to holonification of manufacturing systems was introduced based on an extension of the *Virtual Manufacturing (VM)* concept (Onosato and Iwata, 1993) where manufacturing sub-systems can be classified into four categories: Real Physical System (RPS), Real Informational System (RIS), Virtual Physical System (VPS), Virtual Informational System (VIS). VM makes it possible to simulate manufacturing processes in advance, without using real facilities, and by this, to accelerate the design and re-design of real manufacturing systems.

A fundamental feature of the VM concept is that it realises a one-to-one mapping between the real and virtual systems, i.e. VIS and VPS try to simulate RIS and RPS, respectively, as exactly as possible. The main novelty of the approach described in (Kádár and Monostori, 1998), is the break with the above one-to-one mapping, more exactly the use of the VM concept to control a traditional (centralised / hierarchical) manufacturing system in a holonic way.

The virtual part of the system (Fig. 9) runs in a holonic way and incorporates order management, scheduling and control issues. For the realisation of the virtual part, simulation systems such as the simulation framework described earlier in this Section can be advantageously used. Resource agents which, from technological point of view, correspond to the real resources of the traditional system can be easily constructed by using the object library of the simulation framework (Kádár, *et al.*, 1998). Order management proceeds fully in the virtual system.

Decisions are made in the virtual, holonic system and conveyed to the VIS of the traditional system. The real production situation is sensed by the RPS and forwarded to the VIS, which initiates appropriate measures in a holonic way. As a summary, the traditional system shows holonic behaviour.

The holonic information system tested in a virtual environment has the potential of being used in real holonic systems. Some requirements for this system-level holonification are also given in (Kádár and Monostori, 1998).

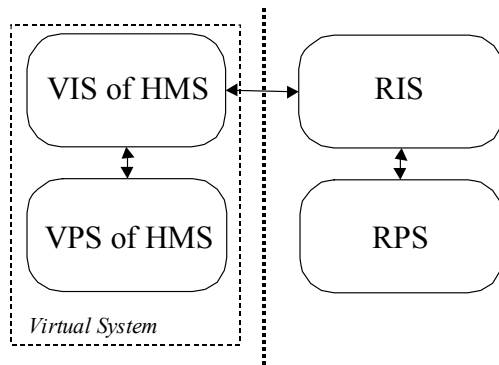


Fig. 9. Concept for holonification of traditional manufacturing systems by using the VM technology

4.4. Approaches to increase the performance of agent-based production system

To overcome the disadvantages associated with hierarchical control several researchers (e.g. Hatvany, 1985; Duffie and Piper, 1986), proposed a heterarchical approach.

Heterarchical control is a highly distributed form of control, implemented by a system of independent co-operating processes or *agents* without centralised or explicit direct control. Control decisions are reached through mutual agreement and information is exchanged freely among the participating agents. The concepts for heterarchical control are derived from biological metaphors and analogies to the free market economy (Vámos, 1983). Therefore, heterarchical control architectures offer similar prospects of reduced complexity, high flexibility and a high robustness against disturbances in manufacturing. As such, there is no need for explicit reactive scheduling.

Experiments (Duffie and Prabhu, 1994) and theoretical considerations (Luh and Czerwinsky, 1994) have partially proven these expectations. However, it has also turned out that heterarchical control, banning all forms of hierarchy, cannot guarantee optimum performance. Even more essential might be that the behaviour of a system under heterarchical control can be unpredictable.

Concept of hierarchy in a distributed system

To combine robustness against disturbances with performance optimisation and predictability the incorporation of hierarchy in a distributed control system was proposed in (Bongaerts, *et al.*, 2000). The resulting control architecture has a basic structure of autonomous co-operating local agents, which are capable of negotiation with each other in

order to achieve production targets. That basic structure is extended with central agents (for instance a scheduler agent) to co-ordinate the behaviour of the local agents. The resulting architecture complies with the concepts of holonic manufacturing. Such a system then has both distributed and centralised control capabilities. The central agents operate concurrently with local agents and contribute to the same decision making processes as the local agents. The local agents maintain their decision making autonomously, but may request *advice* from the central agents. In this way, the central agents can co-ordinate and optimise the overall behaviour of the system.

Learning issues in agent-based manufacturing

It is extremely difficult or even impossible to correctly determine the behavioural repertoire and concrete activities of a multi-agent system a priori (Shen, *et al.*, 2000). In the referred paper important aspects of learning in a multi-agent setting are discussed, i.e. why, when, where and what to learn. In this domain both "*learning from history*" and "*learning from the future*" can be advantageously used. Concerning the latter, let us refer to the simulation framework described in this Section, which can be used as a tool for learning from the future.

In agent-based manufacturing systems a number of system level and resource level parameters can be the subject of a learning process, an important issue is, how to fuse these information.

Having recognised the importance of learning in agent-based manufacturing architectures, research was initiated at the Computer and Automation Research Institute to develop agent-based manufacturing control architectures with increased and more balanced performance. The first results are treated in (Kádár and Monostori, 2001).

CONCLUSIONS

Learning process models, cause-effect relations, automatically recognising different process changes and degradation and intervening in the process in order to ensure safe processes and product qualities are sophisticated approaches with high potential. They are the subjects of intensive research and development work world-wide. The complexity of the problem and the associated uncertainties necessitate the application of *learning techniques* to get closer to *working IMSs*. In correspondence with a recently published larger survey on ML approaches

to manufacturing (Monostori, *et al.*, 1996), the following main trends can be enumerated:

- attributable mostly to the results of ANN research, and in contrast to the situation 8-10 years ago, when they were considered as fields hardly manageable with AI techniques the area of *process modelling, monitoring and control* came to the fore;
- in recent years *ANN based learning* is the dominant ML technique in manufacturing;
- ANNs are natural tools at *lower levels of intelligent manufacturing systems* where abilities of sensor integration, signal processing, uncertainty handling, real-time and adaptive functioning are required, but
- ANNs find their applications on nearly every, also on *non-sensory domains* of manufacturing, as general information processing blocks with learning abilities;
- development and routine production of *programmable ANN chips* (e.g., cellular neural networks (Roska and Rodriguez-Vazquez, 2000) will give a new, spectacular impulse to ANN applications in manufacturing, especially with the rapid spread of *smart sensors*;
- *neuro-fuzzy* approaches manifest themselves as prospective tools of numerous problems in manufacturing *where real-time nature, learning ability, handling of uncertainty and both symbolic and numeric information* are essential requirements;
- as the considerable number of projects *with multistrategy learning* methods shows, the future belongs to these integrated approaches (Egresits, *et al.*, 1998).

Distributed, holonic-like systems represent viable alternatives to hierarchical and heterarchical structures and the corresponding reactive scheduling approaches. Both of these - apparently distinct - lines can be advantageously used in rapidly changing production environments, however, none of them can be regarded as a universal tool. Even the application of such powerful global optimisation techniques as GAs, are not appropriate for very large problems, and as centralised approaches, are not totally devoid of all the known drawbacks of centralised / hierarchical control systems (Monostori, *et al.*, 1998). The multi-agent approach also becomes unrealistic beyond a given problem size, first of all due to the rapidly increasing communication burden. Consequently, both directions crave for some kind of *aggregation* (Van Brussel, *et al.*, 1998). There is a scope for *temporal or permanent hierarchies* also in holonic architectures (Bongaerts, *et al.*, 2000). By this way, the amount of necessary communication can be decreased, and the holonic concept can be

expanded to the level of *extended* or *virtual enterprises*.

A fundamental issue in distributed systems is how to ensure global performance with selfish agents pursuing their own goals (Hatvany, 1985). The integration of scheduling agents as a kind of *staff holons* (Van Brussel, *et al.*, 1998) into the architecture, can contribute to achieving global coherence in distributed systems (Monostori, *et al.*, 1998).

The object-oriented simulation framework described in the paper, is expected to provide the necessary framework for further research addressing such fundamental issues of distributed manufacturing as agent structures, communication protocols, group formation, negotiation, global versus local optima, scalability, system tuning, agents' behaviour, learning at system and agent levels (Monostori, *et al.*, 1996).

The further integration of more traditional AI and ML techniques with the agent-based approach in the field of intelligent machines can be predicted resulting in systems with emergent behaviour (Ueda, *et al.*, 2001).

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