Approaches to coupling connectionist and expert systems in intelligent manufacturing

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Abstract

Artificial neural networks are successfully applied in different fields of manufacturing, mostly where multisensor integration, robustness, real-timeness, and learning abilities are needed. Since the higher levels of the control and the monitoring hierarchy require symbolic knowledge representation and processing techniques, the integrated use of the symbolic and subsymbolic approaches is straightforward. The paper describes two hybrid artificial intelligence systems for control and monitoring of manufacturing processes on different hardware and software bases. The first experiences gained by their usage are outlined. Finally, further possible applications of these hybrid solutions in an intelligent manufacturing environment are enumerated. © 1997 Elsevier Science B.V.

Keywords: Control and monitoring of manufacturing processes; Artificial intelligence; Expert systems; Artificial neural networks; Hybrid AI systems

1. Introduction

In recent years, *artificial neural networks* (ANNs) were successfully applied to monitoring and modelling of manufacturing processes [1]. The main results of these investigations are the following:
· multisensor integration through ANNs;
· classification of wear states of cutting tools;
· estimation of flank wear;

· incorporation of cutting parameters into the learning and classification phases;
· inverse modelling of the cutting process by neural networks; and
· application of inverse models for tool monitoring [2–6].

Investigations confirmed that – similarly to our present conception of biological structures – ANN techniques seem to be a viable solution for the lower level of intelligent, hierarchical control and monitoring systems. Since the higher levels of the control and monitoring hierarchy require mostly symbolic knowledge representation and processing, the inte-

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gration of symbolic and subsymbolic methods was predicted [1,7].

Several techniques for integrating expert systems and neural networks have emerged over the past two to three years [8]:

- *Stand-alone models* of combined expert system and neural network applications consist of independent software components not interacting in any way.
- *Transformational models*: in one direction, *neural networks* are often used to adapt quickly to a complex, data-intensive problem, to provide generalization, and to filter errors in the data. The trained networks are transformed into expert systems for reasons such as knowledge documentation and verification, the desire of stepwise reasoning, and for explanation facilities. Less commonly, in the expert system to neural network transformational model, knowledge from the expert system is used to set the initial conditions and training set for the neural network, and the neural network evolves from there.
- In *loosely coupled models* neural network and expert system components communicate via *data files*. Here, the ANN module can perform *preprocessing*, *post-processing* or *co-processing* tasks.
- *Tight coupling* passes information via *memory-resident data structures* rather than external data files, improving its interactive capabilities.
- *Fully integrated expert system / neural network models* share data structures and knowledge representation. Communication between the different components is accomplished via the dual nature (symbolic and neural) of the structures. Reasoning is accomplished either cooperatively or through a component designated as the controller.

The aim of the paper is to describe and compare two solutions for coupled hybrid AI systems developed mostly for manufacturing and diagnostic applications within the framework of different two- and three-side cooperations between the Institute of Electrical Measurement (EMl), University of Paderborn and the Computer and Automation Research Institute (CAI), Hungarian Academy of Sciences as well as the Institute of Manufacturing Technology, Technical University of Budapest.

2. Concept of hierarchically structured hybrid AI systems for manufacturing applications

A *hierarchical structure* of intelligent machine tool controllers was suggested in [9]. In this scheme, the lower levels consist of adaptive controllers and process pattern recognizers, designed off-line. The higher levels are more global and provide data processing over a longer period of time. The results from the higher levels are manifested as changes in the lower-level parameters. The conclusion of the article is that off-line and on-line learning and self-organizing techniques are crucial for these intelligent controllers to be able to operate machines in optimal conditions.

This approach was generalized in the *concept of a hierarchical monitoring and diagnostic system for manufacturing cells* [10]. Model-based and pattern recognition-based algorithms characterized the lower, machine tool level, which was connected to the cell-level subsystem with symbolic knowledge representation and processing techniques.

In the referred project supported by the European Union, besides the development of neuro monitoring and diagnostic systems [11] on different hardware
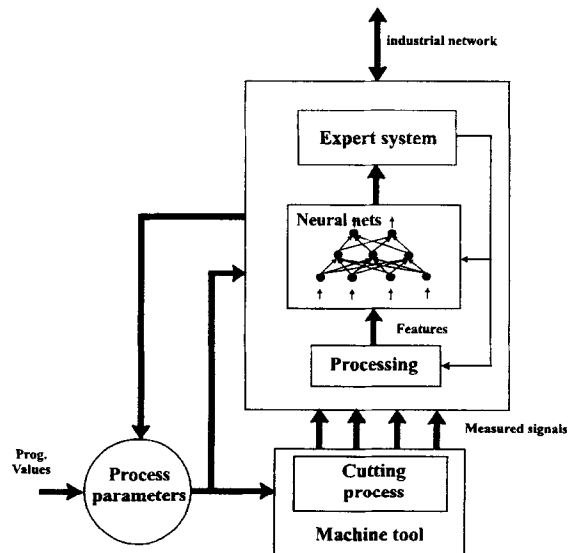

Fig. 1. Control and monitoring of manufacturing processes by a hierarchically structured hybrid AI system.

bases, the *combined use of subsymbolic and symbolic knowledge representing and processing techniques* is attempted. In these hybrid systems, networks outputs are conveyed to an expert system which provides process control information (Fig. 1). On the basis 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.

This *tight coupling* approach has some clear advantages:

- it fits to the monitoring–control hierarchy of manufacturing cells regarding both the form and speed of information processing;
- modular structure enabling and facilitating the use of commercial tools;
- faster development;
- clear interfaces;
- easier integration into the existing manufacturing environment.

In the following, two realizations of this concept will be described.

3. SPURT: a VME bus multiprocessor diagnostic system using hybrid AI technique

3.1. Elements of the system

3.1.1. Hardware

The demand of a diagnostic system dealing with subsymbolic and symbolic systems leads to a VME bus-based multiprocessor system. In order to meet the short response times to the process, which is usually not provided by UNIX, the parallel processor system SPURT (Signalprozessorunterstütztes Realzeit Testsystem; see Fig. 2) has been designed utilizing standard VME bus single-board components as processing units (PUs) for feature extraction and low-level decisions, global memory for fast data exchange and analogue–digital converters (ADC) for data acquisition. This diagnostic tool exhibits a self-developed operational system with dynamic task distribution meeting the real-time requirements.

Fig. 3 shows a view of the modular and mobile system SPURT, which can be installed in manufacturing cell environments.
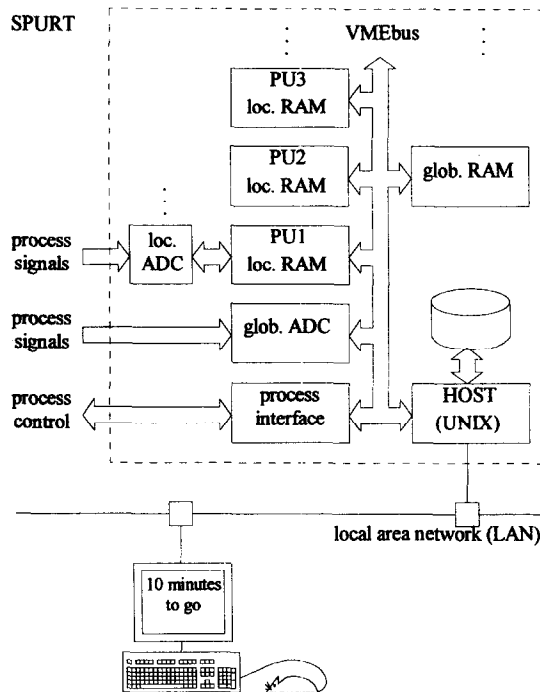

Fig. 2. Scheme of the diagnostic system SPURT.

3.1.2. Software

The diagnostic system software consists of two parts written in C. One part is for solving the tasks of data acquisition, feature extraction and subsymbolic classification. This part is running on the multiprocessor subsystem meeting the real-time demands of the process. All procedures are divided into tasks which can be processed by a single PU. Usually several tasks of one or more procedures can be calculated in parallel on the available PUs. For typical applications the necessary computational power can be provided by a variable number of PUs. The distribution of the tasks is solved by a developed *task management controller* considering the demands of the process as well as the priority of the specific task within the whole diagnostic procedure and is supervised via a link to host.

The other part is the user interface of the multiprocessor system and the expert system KOMRED for the symbolic decision method. These parts are running under UNIX on the host and provide the connection to other computers via LAN.
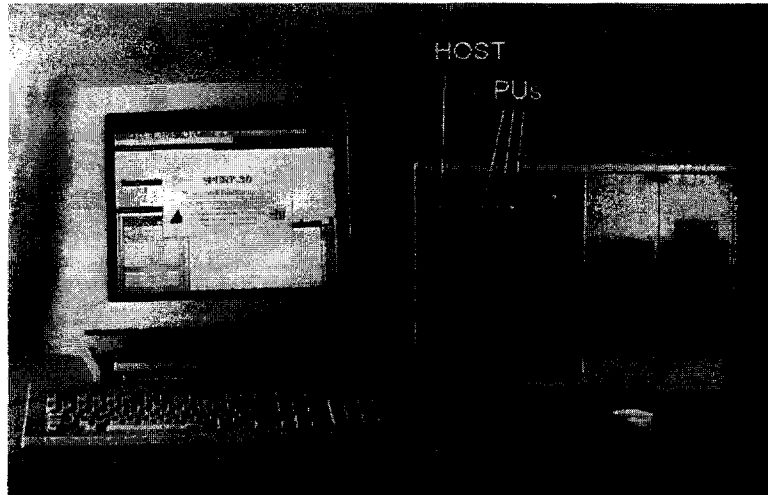
Fig. 3. View of the modular and mobile system SPURT.

3.1.3. Man / machine interfaces, programming

User programs are designed under the UNIX operating system running on a 32-bit MC 68040 board serving as host computer and being highly supported by the iconic facilities of the X-Window system. Due to the multitasking capabilities this diagnostic tool can easily be integrated into computer networks.

Flexibility with respect to the applied diagnostic problem is further increased by the easy-to-use programming language MODAL (MOdular Diagnostic Application Language), which provides macro commands for all operations necessary for data acquisition, pre-processing, learning and classification and also for graphical data representation. Application-specific programs can be realized in a simple manner by combining these macros. Special parallel programming knowledge is not required.

A compiler developed for the conceptualized system running under UNIX transforms the job thus specified after the necessary syntactic and semantic checks to an output language used by the distributed schedulers of the various single-board computer subsystems in order to map the different tasks dynamically to the available processors. The distribution is automatically performed by the designed "*task scheduler*" of the multiprocessor system.

3.2. Process control and monitoring facilities

The multiprocessor system SPURT was applied to process monitoring of a CNC lathe (see Fig. 4).

All tasks for data acquisition, feature extraction and the subsymbolic decision yielding well-known process parameter values, e.g., flank wear of the work tool or remaining cutting time, are calculated and transferred to the host of the system.

There, comparisons with mathematical models of the turning process are accomplished [12,16,17] and after conversion of numerical values into symbolic representations the information is transferred to the tightly coupled expert system KOMRED with data exchange via memory-resident data structures (see Fig. 5).
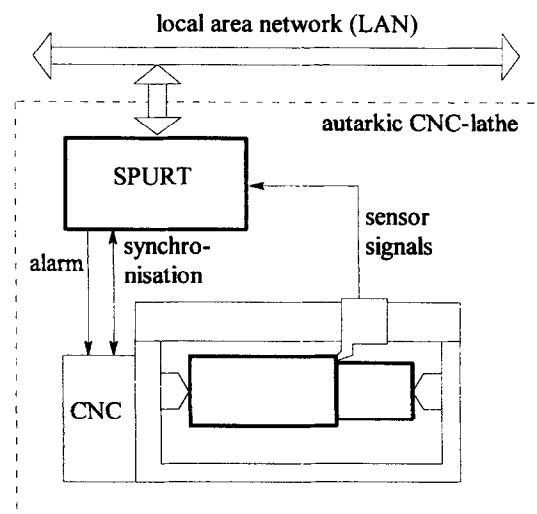

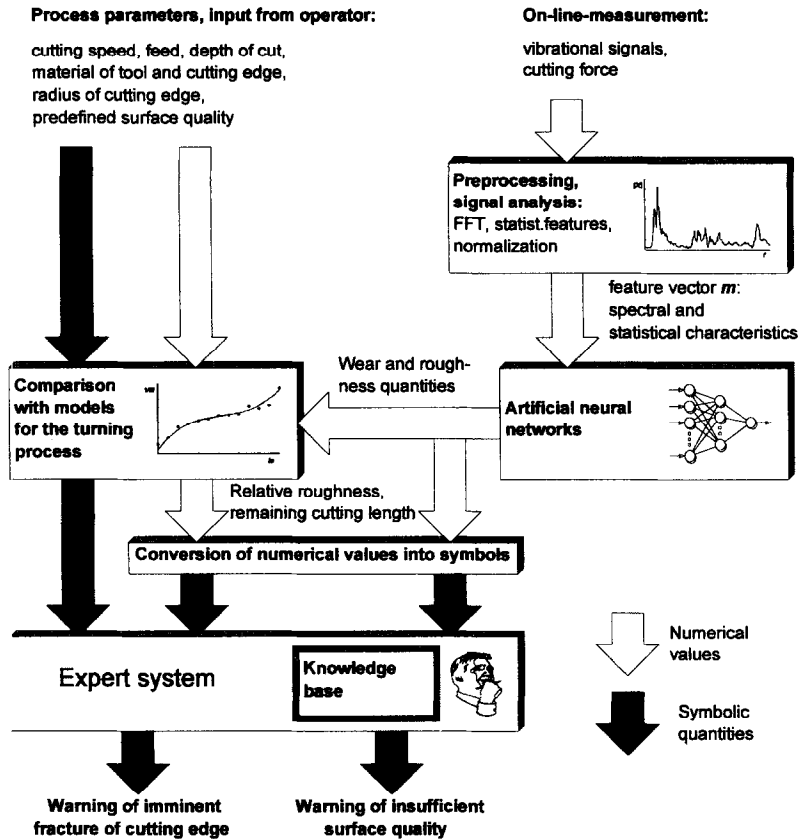Fig. 4. SPURT applied at a CNC lathe [12].

Fig. 5. Scheme of the tightly coupled diagnostic system.

Based on the available information, warnings of imminent fracture of the cutting tool or insufficient surface qualities as well as an estimate for the remaining time for the next tool exchange are determined by the expert system and displayed to the operator. The information can be used for process control purposes within the production cell and the higher level of production control, respectively.

4. HYBEXP: a PC-based hybrid control and monitoring system

4.1. Elements of the HYBEXP system

In the realization developed in the Computer and Automation Research Institute, Budapest, an artificial neural network simulator called NEURECA constitutes the lower, subsymbolic level [13,18,19]. It provides the following main functions in an integrated framework:

- definition of different statistical and spectral features for various channels (Fig. 6);
- on-line feature computation;
- automatic feature selection;
- manipulation, visualization of pattern files;
- ANN learning with back-propagation (BP) algorithm;
- classification, estimation of unknown patterns;
- standardized (DDE) interfaces to other programs, etc.

NEURECA was written in C + + using its object-oriented nature enabling one to dynamically vary the network structure during learning and to implement different ANN models including *neuro-fuzzy* approaches [14].
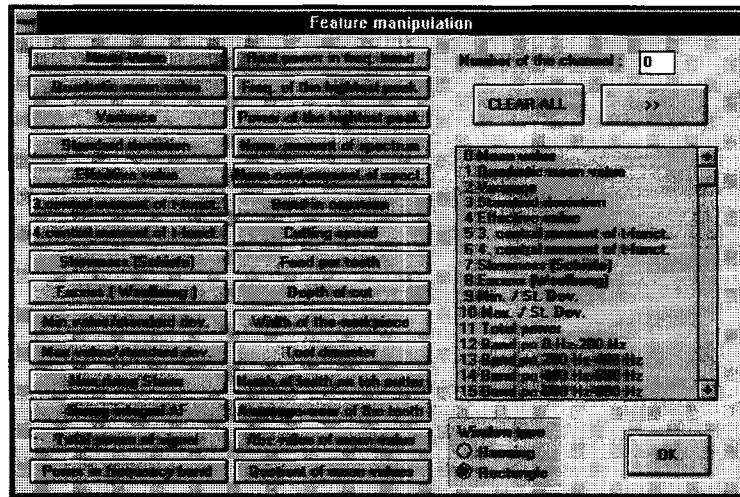
Fig. 7 illustrates some functions of the system

Fig. 6. Feature definition in NEURECA.

during learning, e.g. visualization of the network (strengths of weights and node activations are characterized by different colours), the normalized inputs and outputs, the error curve during learning, visualization of the network's outputs and the corresponding target values, etc.

The system (and its predecessor) was successfully applied to monitoring and control of different manu-
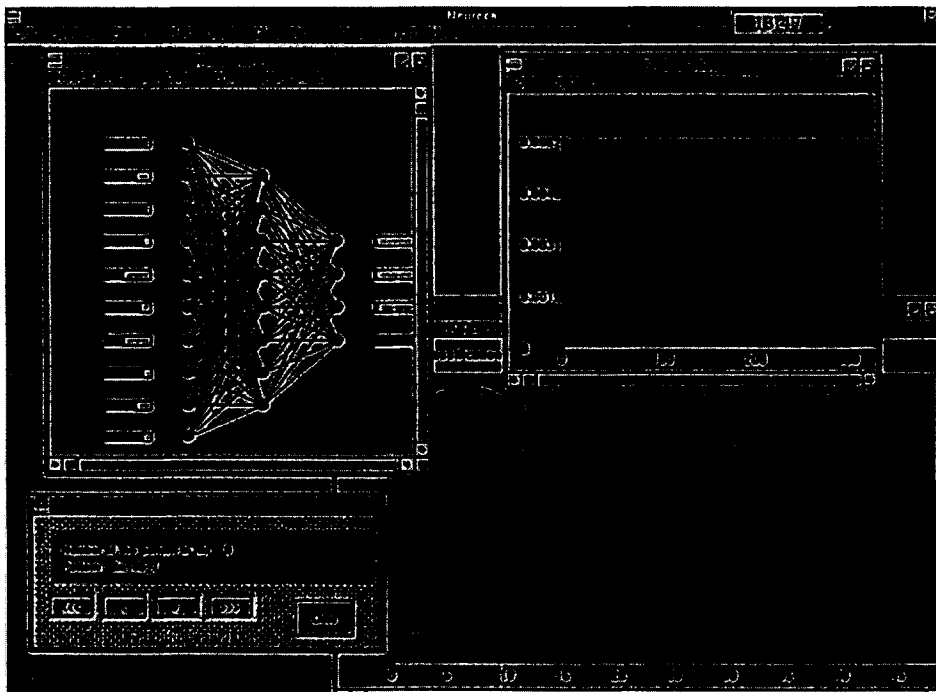

Fig. 7. Some visualization facilities of NEURECA.

facturing processes (turning, milling) [6]. Fig. 7 refers to the four-class recognition problem of milling tools (sharp tools, tools with an average wear of teeth of 0.25 and 0.45 mm respectively, and tools with broken (missing) insert).

The *higher, symbolic* level is based on the commercially available GoldWorks III expert system shell [15]. GoldWorks provides frame-level and Lisp-level access to DDE files, so GoldWorks applications can directly access data in other applications through Microsoft's DDE interface.

Fig. 8 illustrates the coupling and functioning of different submodules of the developed hybrid system. This hybrid solution incorporates the NEURECA neural network simulator (A) at the lower level and the symbolic part (B) at the higher level.

These two levels communicate with each other through Microsoft's DDE interface (I). 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), enlightening the test and demonstration of the system (see section 4.3).

4.2. Control and monitoring of the milling process by the HYBEXP system

Configuration of the SIMURECA and NEURECA subsystems can be initiated from the symbolic level (Fig. 9). Type of manufacturing (e.g., turning, milling), the signals to be measured (e.g., force,
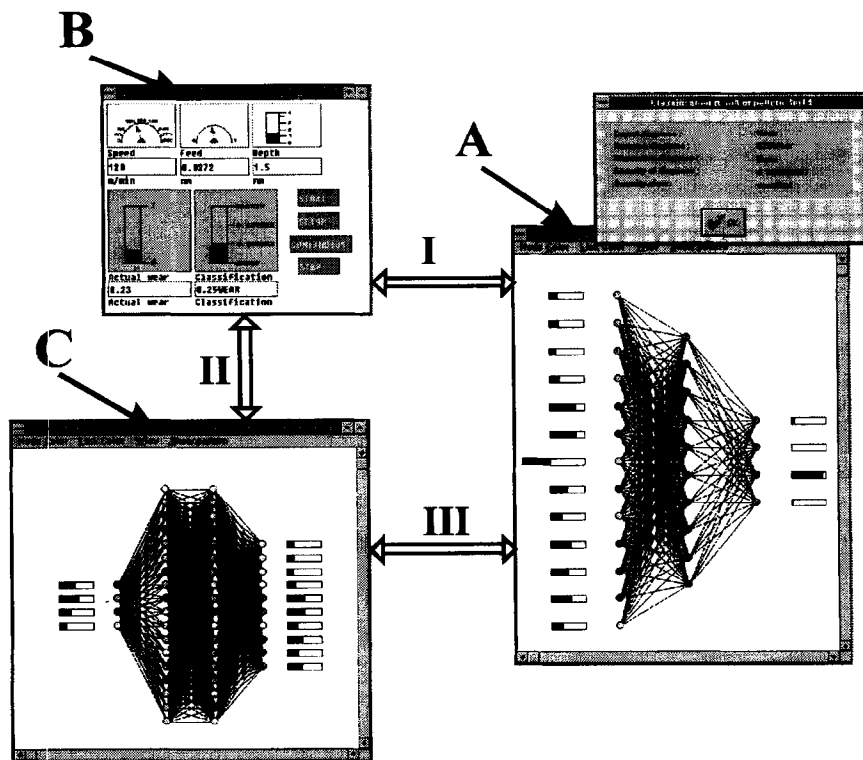

Fig. 8. Components of the HYBEXP PC-based hierarchically structured hybrid AI system.

Initial Input

Please configure the system?

○ **TURNING**
● **MILLING**
Type of manufacturing

⊠ **FORCE**
⊠ **VIBRATION**
Signals

● **CLASSIFICATION**
○ **ESTIMATION**
Output type

○ 6
● 10
○ 12
○ 15
○ 21
No. of features

● YES
○ NO
Characteristics

OK   **Cancel**

Fig. 9. Configuration of NEURECA and SIMURECA from the symbolic level of HYBEXP.

vibration), the number of considered features and the type of task (classification or estimation) to be fulfilled by NEURECA can be defined. All of the other tasks (e.g., activation of corresponding signal processing routines, neural networks, communication between the subsystems) proceed automatically. Behind this configuration process there are rules that govern this process.

According to previous investigations [3,6] 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 NEURECA additionally incorporate cutting parameters to indirect signal features. Models for both classification and estimation can be used. They are selected by the hybrid part of the HYBEXP during the described configuration process.

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) different decisions can be made. HYBEXP can initiate, for example, machine stop, tool change, modification of cutting parameters (AC control) or change of parts to be machined. Using the high-level explanation and visualization capabilities of GoldWorks different levels of information can be forwarded to

the user (Fig. 8), or HYBEXP can work also as a *decision support system.*

4.3. Simulation of manufacturing processes by ANN technique

Simulation of manufacturing processes is an open problem with high importance. There are a number of analytical methods but none of them proved to be reliable enough. Adaptability is required, i.e., systems which can adapt themselves to the varying manufacturing conditions. With the version of NEURECA (SIMURECA) an attempt was made to apply ANN techniques in simulation of manufacturing processes (Fig. 8). On the basis 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.

Using training patterns which characterize a sufficiently broad range of cutting parameters, reliable estimates of force and vibration signal features have been generated for face milling. These estimates can be used also for process planning purposes. On the basis of these favourable results, the simulation of ultra-precision turning has been initiated.

4.4. Experimental results

The neural part of HYBEXP was extensively used for modelling and monitoring of turning and milling [6]. Favourable results have been obtained also for classification of tool states and for the estimation of tool wear. The incorporation of process parameters (e.g., feed rate, cutting speed, depth of cut) into the networks' inputs resulted in models which function over a broader range of process parameters.

The set-up illustrated in Fig. 8, which incorporates the simulation of the machining process, proved to be extremely useful in the development and test phases of the hybrid system. This solution can be regarded as a kind of virtual manufacturing. On the basis of the information provided by the neural part, the rules of the symbolic level fired appropriately,

and initiated, for example, tool change or modification of process parameters.

As a further development, the symbolic part of HYBEXP has been expanded in order to manage cell-level functions, e.g. tool management and scheduling. These developments will be published in the near future.

5. Conclusions

Although ANNs have been successfully applied to different areas of manufacturing, mostly where *multisensor integration*, *robustness*, *real-timeness* and *learning abilities* were required, they cannot be considered as universal tools for intelligent manufacturing systems. Since the higher levels of the control/monitoring hierarchy need symbolic knowledge representation and processing techniques, the integrated use of the symbolic and subsymbolic approaches is straightforward [1,7].

The paper describes two hybrid AI systems for control and monitoring of manufacturing processes on different hardware and software bases. The first experiences gained by their applications are described. Further projects were initiated to investigate the applicability of the outlined hierarchical approach of hybrid AI systems:

- in production control and scheduling of manufacturing systems;
- in distributed control systems incorporating numerous ANN models;
- in holonic type systems.

It is expected that the hybrid AI approaches outlined will be able to provide sufficient frameworks for the solution of numerous problems in manufacturing, and to contribute to the future realization of intelligent manufacturing systems.

Acknowledgements

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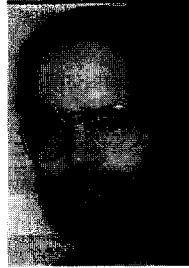
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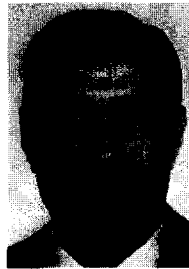

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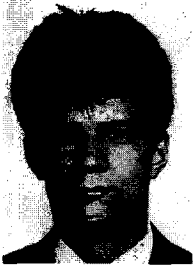
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