# SMART NEURO-FUZZY BASED CONTROL OF A ROTARY HAMMER DRILL

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***Abstract*- In order to reach optimal drill penetration using a rotary hammer, it is necessary to control the two variables, rotational speed and strike rate, of the rotary hammer in such a way that by applying minimal guidance and recoil power, a maximum drill penetration rate can be achieved in the rock. An optimal drill penetration rate is attained through using a given combination of rotational speed and strike rate. Changes in the drill diameter and/or material hardness lead to a false adjustment of the system which has to be re-optimized by an intelligent re-adjustment of the two servo-controlled drives. To achieve a flexible and automatic adaptation of rotational speed and strike rate of the rotary hammer to different material and tool types, an adaptive multi-sensor drive control based on a self-learning neuro-fuzzy component has been developed by IITB in cooperation with an industrial partner.**

## I. INTRODUCTION

Mechatronics is becoming ever more widely used in the products on the consumer goods markets, where efficient control and guide processes can be implemented using very inexpensive sensors, processors, and actuators. This is particularly true for the market in semi-professional products, where an increasing client base is prepared to spend money on products that combine novel, useful functions and characteristic features. The rotary hammer is representative of this product group.

To achieve optimum drill performance, it is necessary to set the two variables ‚rotational speed of the drill' and ‚strike rate of the hammer' of the tool, whether guided by human hand or robot, in such a way that, with a minimum of guidance and recoil power, maximal drill penetration can be achieved in the rock. The 'mechanics' of a system consisting of the guiding human (or robot), the rotary hammer, and the rock create a complete multi-body system during the drilling process, which, at any given combination of rotation rate and strike rate, delivers an optimal drill penetration rate. Changes in the drill diameter, the type of rock, or the drilling pressure result in a false adjustment of the multi-body system, which needs to be re-optimized by an intelligent re-adjustment of the two servo-controlled drives.

To achieve a flexible and automatic adaptation of the strike and rotation rate of the rotary hammer to different material and tool types, the IITB in cooperation with an industry partner developed and built a prototype of an adaptive, multi sensor drive control. The proposed solution envisages a self-learning neuro-fuzzy component which can identify the given parameters from the sensory signals of the integrated system of 'operator-rotary hammer-wall'. The optimal strike and rotation parameters can then be read from a look-up table and adjusted automatically [9]. The multi-sensor intelligent rotary hammer is thus capable of determining the optimal operating parameters for each type of rock and tool and to adjust them automatically. In addition to maximizing the drill capability, other quality requirements such as the minimization of energy consumption of battery-driven tools can be integrated into the optimization considerations. The adjustment of the drill and strike rate of the rotary hammer can be done using two independently controllable drives or manually (using guidance display).

## II. SOLUTION CONCEPT

The neuro-adaptive concept is based on the following steps (cf. fig. 1):

In the first step of the multi-sensory real time process diagnosis, drill diameters and rock types are diagnosed quickly and accurately from a variety of available sensor signals using self-learning neuro-fuzzy real time diagnostic processes. It is assumed that the rotary drill is equipped with the suitable sensors to measure the strike rate, the rotation rate, the vertical and lateral acceleration as well as the electrical output, the cost of which is acceptable in the semi-professional market. Information from the real time diagnosis, the process mode and the deviations from the planned process, respectively, serves as input data for the optimization of the rotary drill operating parameters. The real time diagnostic process consists of two sequential steps: the generation of characteristic features and the interpretation of characteristic features. Similar neuro-fuzzy based real time diagnostic processes have been used successfully at the IITB for the surveillance of other mechatronic systems [3, 4] and operational processes in industry [1, 2].

In the second step, the optimal operating parameters are determined for the given drill diameter and rock type. The characteristic diagrams necessary for the optimization of the operating parameters are determined through a series of tests and are then saved to look-up tables. The optimization includes the determination of the minimum or maximum values of the characteristic curves on the basis of optimization algorithms. This results in optimal strike and rotation rates, i.e. the optimal performance of the rotary hammer. This optimization can be achieved in various ways depending on the type of rotary hammer. On a system with two separately guided electrical drives, optimized strike and rotation rates can be set automatically using conventional drive controls. On the traditional single-motor rotary hammers with multi-stage or continuous drives, the optimal operating parameters can be set manually, if necessary, using guidance displays.

## III. ROTARY HAMMER SYSTEM CHARACTERISTICS

The characteristic movements of a rotary hammer, whose percussion drill penetrates the rock guided by humans, is extraordinarily complex. This complexity stems, on the one hand, from the elastic interaction of numerous partial masses consisting of the rotary hammer, the human arm, and the rock to be worked (cf. fig. 2). On the other hand, the movement characteristics of the elastically-coupled system "operator-rotary hammer-wall" is characterized by considerable non-linearities, particularly because of the interplay and the friction of the tool parts hitting each other (floating piston, percussion piston, drive piston), the non-linear compression action of the electro-pneumatically driven percussion piston, and above all because of the hammering-cutting action of the drill in the borehole.

The action of the complex, non-linear multi-body system is especially sensitive to changes in the parameters drill diameter, rock type, and contact pressure. If one of these parameters is altered, it can lead to considerable impairment of the drill progress and the vibration action.

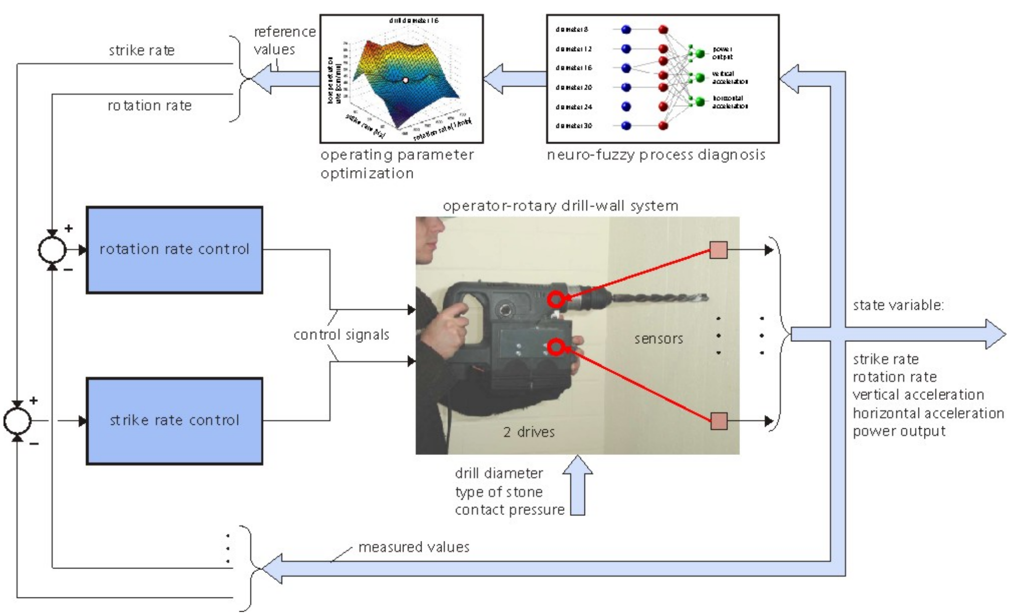


Fig. 1: Schematic representation of the neuro-fuzzy based drill control concept

Numerous modeling suggestions have been published in an attempt to describe and simulate the movement characteristic. These can be divided into two groups according to the methods used:

- *Elastic multi-body models*, which specify above all the simulation and optimization of the vibration characteristic features of the rotary hammer housing and the human arm.[5, 6]
- *Body shock models*, based on Shock-Wave-Theory [11] , which focus on the description of the energy transmission during the impact of the drive piston from the percussion and floating pistons to the drill bit [7,8].

Both types of models are each suitable only for the analysis of certain research questions and partial areas of the complex overall system. Generic models, which comprehensively describe and simulate the dynamic and stationary drill characteristics of the complete system „operator-rotary hammer-wall“ as a function of the drive controlled strike rate BPS [Hz] and rotation rate RPM [1/sec], have not been published to date.

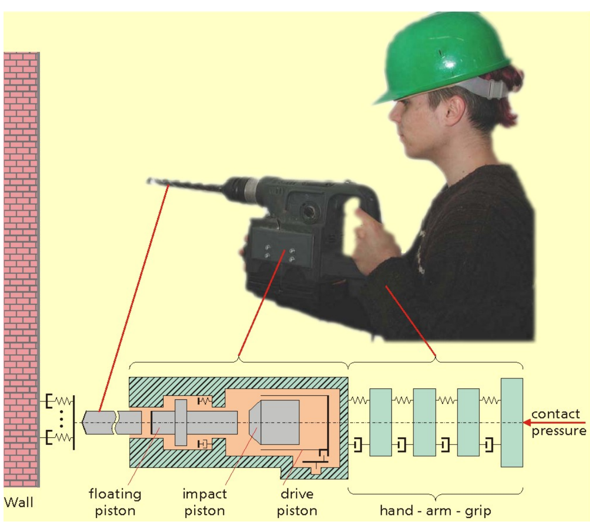


Fig. 2: Schematic representation of the complex multi-body operator-rotary hammer-wall system

As the neuro-fuzzy-based adaptation concept introduced in this paper is less concerned with the dynamic characteristics but is primarily interested in the stationary dependency of the drilling penetration p [cm$^3$/min] on BPS and RPM, this family of characteristic curves was determined experimentally through a systematic series of tests. To this end, a test environment was created at the IITB, in which exactly-replicable drilling experiments can be carried out and measured using different BPS- and RPM-characteristic features with different drill diameters, rock types, and contact pressures.

To determine the movement and power characteristic features as well as other relevant process information, the rotary hammer and rotary hammer guide were outfitted with different sensors. The sensors registered in particular the lateral and vertical acceleration, the strike rate BPM, the rotation rate RPM, the motor capacity and power requirements, the operating temperature and the bore penetration rate p. The BPM-and RPM- desired values were programmed in.

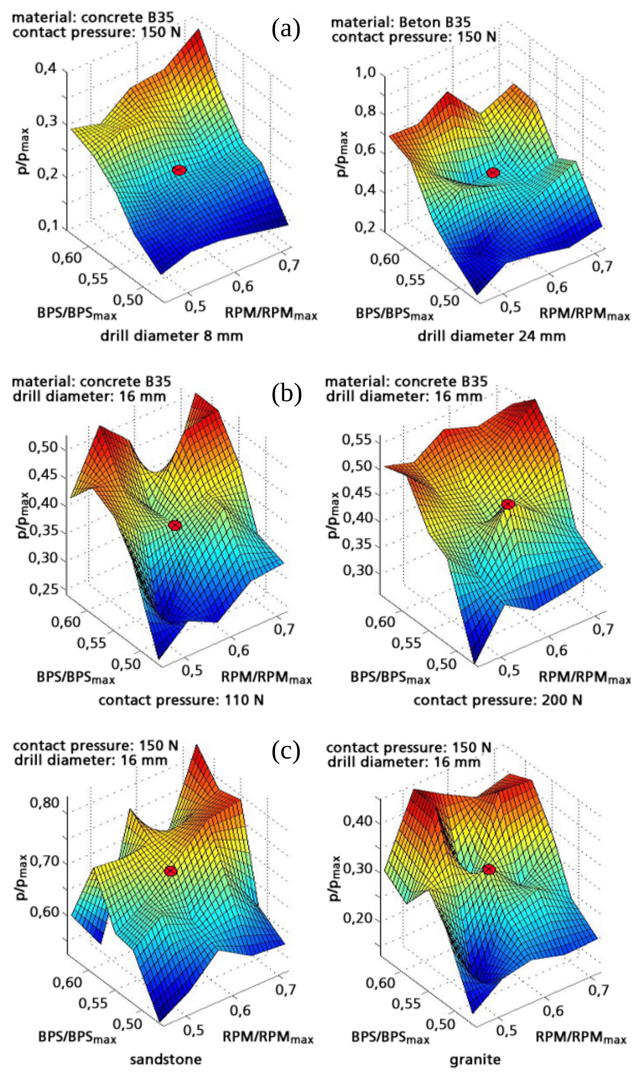


Fig. 3: The measured drill penetration p, as a function of strike rate, BPS, and rotation rate RPM, using different (a) drill sizes (b) rock types and (c) contact pressures

To describe the system performance for the most representative spectrum of process parameters, drilling experiments were carried out for all relevant rotation rate and strike rate values by varying types of materials (concrete, granite, sandstone), drill diameters (8 to 30 mm), and contact pressures (110 N to 200N).

The families of characteristic curves shown in fig. 3 indicate that the drill penetration p has a strong non-linear dependence on BPS and RPM. By varying the three dominant influence parameters of drill diameter, type of rock, and contact pressures, the family of characteristic curves and their maxima change considerably. The nominal (rigid) parameters (BPS, RPM) can vary considerably from the respective optima. That is, a suitable optimization potential for a multi-sensor neuro-fuzzy adaptation of the working parameters exists. To effect a practical realization of an adaptive real time optimization of the BPS- and RPM nominal values for the drive guides, the controlling parameters must be determined through a sensor based neuro-fuzzy classification. (cf. fig. 5). Then the optimal operating parameters are determined from the family of characteristic curves saved as a look-up table (cf. fig. 3) and transmitted to the drive control.

## IV. Neuro-Fuzzy-Classification

For the real time determination of the desired parameters –drill diameter, rock type, contact pressure- fuzzy-based diagnostic methods are particularly well suited because of the inherent fuzziness of the sensor characteristic features. The measurement data shown in fig. 4 of various tests (the drill diameter was varied here) illustrate this. A self-learning neuro-fuzzy method is used because the 'manual' linking of the numerous sensor characteristic features using fuzzy rules can be very time-consuming, and because the required a priori information is not available.

The multi-sensor real time diagnostic process developed at the IITB, which is also used in the of observation of industrial operating processes [10], is made up of two consecutive steps, the generation of characteristic features and the interpretation of those characteristic features.

The generation of characteristic features serves in the processing of the measured process signals. From the multitude of available signals, the relevant signal characteristic features are extracted and summarized in a characteristic features vector of smaller dimensions. To generate characteristic features the following three processes are most often applied: signal-based processes (e.g. fuzzy-based limiting values, trend, and spectral or wavelet analyses), model-based processes (e.g. Kalman Filter) and knowledge-based processes (e. g. expert systems).

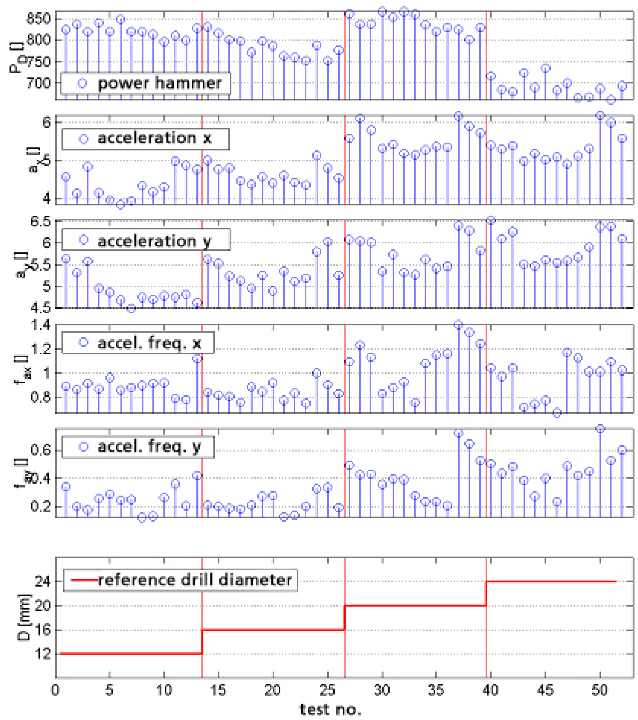


Fig. 4: Measured sensor parameters for different drill diameter

The second step, the evaluation of characteristic features, is a logical decision process which transforms quantitative knowledge into qualitative knowledge. The goal is to decide if and at what point a specific failure or a process phase occurred. To this end, static methods (e.g. generalized likelihood ratio test) and/or characteristic features-based pattern recognition methods (e.g. Bayes-Classifiers, Fuzzy-Logic or neural networks) can be used. Because of the inherent fuzziness of the sensor information used here, neuro-fuzzy methods offer considerable advantages.

On the one hand the association of a certain process phase in the form of association functions μ(x) is described fuzzily, on the other hand, the connection between the characteristic features and the process phases to be classified in the form of linguistic rules is defined; i.e.:

*if* *(characteristic 1 = medium) and*
*(characteristic 2 = large) and …*
*then* *(drill diameter = 12 mm)*

Another advantage is the interpretability of the fuzzy decision module; the characteristic features can be easily modified by the developer; besides, it is possible to simply integrate existing expert knowledge in the form of linguistic rules.

To aid in the implementation of the fuzzy interpretation modules, the neuro-fuzzy formulation NEFCLASS (NEuro-Fuzzy-CLASSification) is used [10, 2]. This hybrid neuro-fuzzy model is based on the generic model of a three-layered FL Perceptron, permitting the interpretation of behavior in the form of linguistic rules.The observed learning algorithm of the NEFCLASS model is capable of both learning the rules as well as adapting the parameters of the association functions *m(x)* underlying the rules. The formation of the rule basis can be made on the one hand based on expert knowledge, but it can also be generated incrementally without prior knowledge. The result of the learning process is an interpretable fuzzy interpretation module (cf. fig. 5). For optimal transparency, only the identification of drill diameters is illustrated here.

## V. Implementation and Results of the Prototype

A prototype was built for the experimental testing and validation of the neuro-fuzzy based solution. The developed real time capable C-software was implemented on a PC-based real time capable rotary hammer control. The neuro-fuzzy classification modules are based on the training data of the three most important parameters: drill diameter, rock type, and contact pressure. The parameter-specific family of characteristic curves and their optima were realized in the form of look-up tables. The strike and rotation values (BPS*, RPM*) were plugged in as desired values to the conventional PID and rotation rate regulators (cf. fig. 1).

For the experimental testing and validation of the neuro-fuzzy software, which was developed in the IITB test environment on the basis of systematic, exactly-replicable test series, numerous manual drill test series were carried out with a variety of users (cf. fig. 6). Although the eight users differed markedly in both weight and method of guiding the drill, the neuro-fuzzy software developed under lab conditions achieved excellent classification results, as the representative measurement in fig 8 illustrates. For approximately 160 drill actions with four different drill diameters, only very few mis-diagnoses occurred; these are negligible as a diagnosis was made in each case only between adjacent drill diameters.

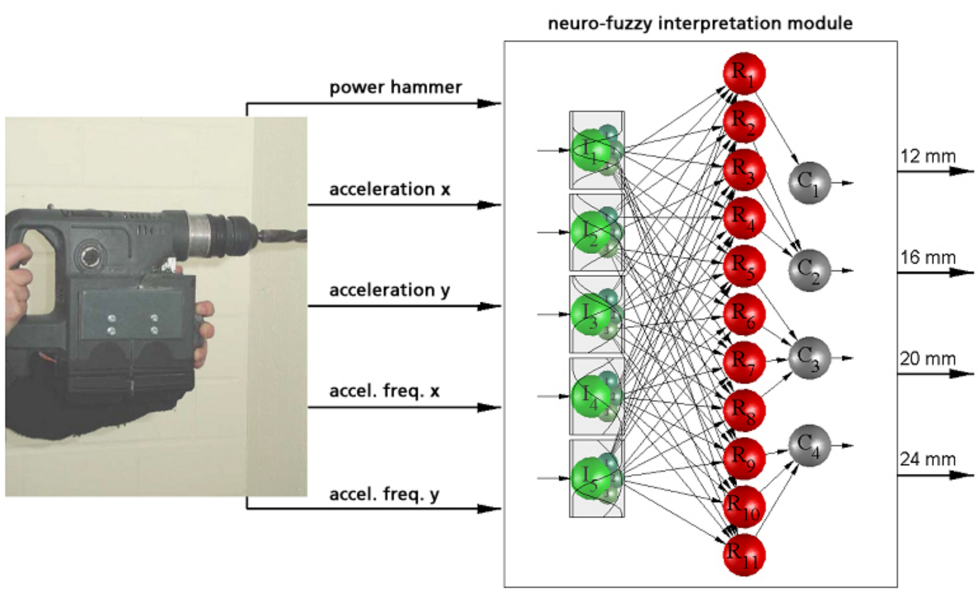


Fig. 5: Self-learning neuro-fuzzy interpretation module for the classification of drill diameters

## VI. SUMMARY

This paper introduces a novel concept for the self-optimizing movement control of a rotary hammer. The solution concept is based on a real time capable, multi-sensor neuro-fuzzy process diagnosis with resulting optimization of work parameters. The realization of the concept presupposes separately controllable strike and rotation drives with integrated sensors and a micro-controller. The efficiency and strength of the prototypically realized solution was successfully proven on the basis of numerous manual drill experiments.

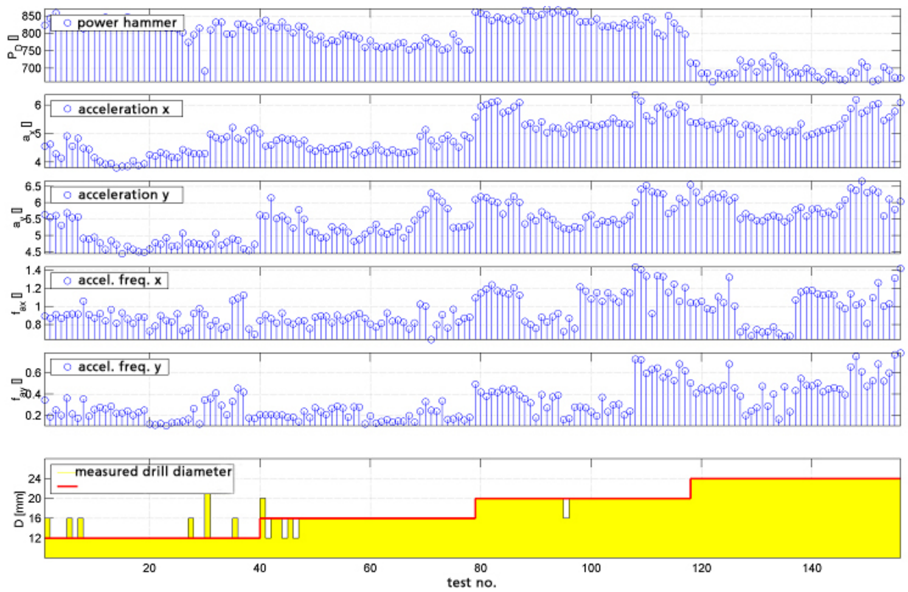


Fig. 6: Representative results in manual drilling tests

## REFERENCES


[1] Frey, C.; M. Sajidman and H.-B. Kuntze: "A Neuro-Fuzzy Supervisory Control System for Industrial Batch Processes". Proc. 9th IEEE Int. Conf. on Fuzzy Systems FUZZ'2000, May 7-10, 2000 San Antonio (USA), pp. 116-121

[2] Frey, C.; Kuntze, H.-B.: "A neuro-fuzzy supervisory control system for industrial batch processes". IEEE Transactions on Fuzzy Systems, Vol. 9 (2001) No. 4, August, pp. 570-577

[3] Kuntze, H.-B.; Haffner, H.: "Experiences with the development of a robot for smart multisensoric pipe inspection". In: Proc. 1998 IEEE International Conference on Robotics and Automation, Leuven/Belgium, May 16-20, 1998, Vol. 2, pp. 1773-1778

[4] Munser, R.; Kuntze, H.-B.; Hartrumpf, M.; Frey, Chr. W.: "Ein modulares Multisensorsystem für Rohrinspektions- und Rohrsanierungsroboter". In: Proceedings 16. Fachgespräch "Autonome Mobile Systeme" (AMS 2000), Karlsruhe, 20.-21.11.2000

[5] Guzella, L.; Schaer, R.; Richter, M.: "Aktive Nachbildung des menschlichen Hand-Arm-Systems". VDI-Berichte Nr. 1094, 1993, S. 615-624

[6] Riederer, H.: "Untersuchungen zur Dynamik elektropneumatischer Bohrhämmer". Dissertation Universität Dortmund, , 1984

[7] Vonnemann, G.: "Energetische Betrachtungen zum schlagenden Bohren". Dissertation Universität Dortmund, 1977

[8] Hecker, R.: "Stoß- und Schallprobleme beim schlagenden Bohren". Dissertation Universität Dortmund, 1982

[9] Frey, Chr.; Kuntze, H.-B.; Jacubasch, A.; Plietsch, R.: "Optimierungsverfahren zur Regelung des Betriebszustandes einer geführten Werkzeugmaschine mit einem rotierenden und Schlag-beaufschlagten Werkzeug während eines Bohrvorganges". Patent der Fraunhofer-Gesellschaft und der Firma Black & Decker, Anmeldetag: 30.08.01, Amtliches Aktenzeichen: PCT/EP01/10018

[10] Nauck, D.; Klawonn, R.; Kruse, R.: "Neuronale Netze und Fuzzy Systeme. Vieweg Verlag, 1994

[11] Cremer, L.: "Körperschall". Springer-Verlag Berlin, 1967