Cognitive Parameter Adaption in Regular Control Structures
Using Process Knowledge for Parameter Adaption

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Abstract: The colour control system of an offset printing machine is one example, where modern information processing technologies allow an improved process control and higher resource efficiency. It is not possible to measure the printing quality during production start. So no regular closed loop control can be used. For better system behaviour a simulation model is integrated to calculate the printing quality at any time. To get an optimal process performance, a high simulation quality must be ensured, which includes a compensation of process simulation inaccuracies as well as variable influences. Therefore a cognitive system is installed, which measures the most important influences like the used paper and many other process parameters. After each production the right model parameters will be calculated by identification algorithms. So a data set with influences and parameters is available. For the next production run the best-fitting parameters for the simulation model can be calculated by a Neural Network. Additionally wear and deposits, which change the machine's performance, can be compensated. The simulation accuracy and the process control quality rises, which enables a faster run-up. Savings of paper, ink, energy and time allow an economic application of this control concept.

1 INTRODUCTION

1.1 Linear Control Theories vs. Methods of Machine Learning

Controllers are often applied in technical devices and industrial machines. The controller type depends on the task. In many processes it is sufficient to use standard PI- or two-level controller. Therefore a closed control loop is essentiell, what means that the process output has to be measured permanently and fed back into the control system.

There exist several concepts to parameterise the controller to ensure stability and dynamic system behaviour. Furthermore powerful computer systems, powerful libraries and high sophisticated software tools are available to setup a complete controller in an easy and fast way.

Although conventional controllers can be used for many applications there are also disadvantages. To use standard control theories, the developer needs to know the transfer function of the machine as well as the process outputs at any time. Furthermore the system behaviour has to be nearly time invariant and approximated as linear.

When one of these conditions is not given, more sophisticated methods have to be taken into account (Hafner, 2009); (Ramesh, 2002). If there is no formal system description, machine learning methods can be used. The most popular type is the Neural Network (Huang, 1994); (Moon 2008); (Rangwala, 1989).

A self-learning system has two states in general. At first it has to be trained with data representing the desired behaviour, the so called training set. In the training sequenzce internal parameters or structures will be changed, till the Neural Network (or all other types of supervised learning methods) gives similar values like the training set (Guanyuz, 2012). When this step is finished, the system can be used to calculate outputs to familiar or to new inputs. The quality of the system strongly depends on the training set. Additionally the optimal net topology and a successful training period cannot be predicted at all. If a self-learning component is used in a control system, the quality of the complete control system can vary (Rajagopalan, 1996). A

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consequence is that the whole system can work inaccurately or becomes instable. Furthermore it is difficult to evaluate the quality of the system (Suzuki, 2011). Moreover there exists only low knowledge about learning systems in the industry, because practical applications are implemented only seldomly in this way.

1.2 Control Structures in Modern Printing Machines

With powerful web presses paper and foils are printed in big lots in a short period of time. There are several control circuits included for printing, cutting and regulating the speed and position of the paper web. For the printing quality the so called optical density is one of the most important control parameters, which expresses the amount of colour on the paper and the optical impress of the printed sheet.

An offset printing machine has four printing units for each colour black, cyan, magenta and yellow. Each printing unit is subdivided in up to 40 zones side by side, because the images require varying amount of ink for each zones. Each zone has its own ink valve, which can be set individually to asure the correct amount of ink according to the printing image. The setting of these valves is called "zone opening" and can be set through the control system. The second setting is the speed of the ink fountain roller, which is equal for all zones. A higher optical density can be reached by a higher zone opening or higher roller speed. Both need to be set correctly to achieve a high printing quality for the product.

The measurement device for the optical density needs a specimen field on each sheet. At the beginning of the printing process the optical density of this field is too low to be detected by the sensor. In this time no optical density can be measured and thus the control circuit is not closed. It is state of the art to use predefined values at the beginning till the density is high enough to be detected by the sensor and close the control circuit. From this point of time the controllers for the printing quality and the sheet cutting start working. It has to be considered, that there are additionally big dead times according to the machine size, which make the control process less stable and slower.

The consumables and environmental conditions like the ambient temperature or humidity also have a big impact on the printing process.

To prevent an instable behaviour at any time, the controller is adjusted conservatively. Between start-up of the machine and reaching the desired optical density all sheets need to be discarded, because their quality level is too low. Figure 1 show the start-up-period of one zone.

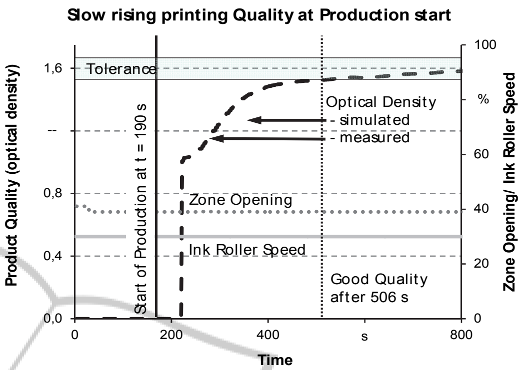

Figure 1: Not acceptable printing quality at the beginning.

The production starts at t = 190 s. At the first 230 seconds no measurements of the optical density are possible. At t= 500 seconds the optical density is in the tolerance, so that the product can be sold. Additionally the zone opening and the ink roller speed is shown, which stay at a static value at the beginning.

2 OBJECTIVES

For increasing the resource efficiency and reducing the production costs, an improved control system is needed to speed up the starting process for a higher printing quality in less time. Furthermore, diverse influences need to be taken into account to heighten the stability of the control system.

3 APPROACH

3.1 General Concept

To build up a stabil and faster control system it is essential to get a closed loop, what means, that output values are available within acceptable time. In figure 2 all elements of a cognitive model based control system are shown, which enables these needs.

A simulation model calculates the output of the real process in that time, when no measurements can be taken in the machine. The measured process output, the optical density, is just needed for tracking the model to the real printing machine (Rae, 1996). Both, the model and the controller are conventionally designed as regular linear systems. Because there are many parameters influencing the system behaviour, the simulation model needs to be adjusted to behave like the real machine. For this, a self-learning adaption mechanism is used to estimate the real machine parameters on basis of former productions. The simulation model parameters will be changed, also like the controller parameters.

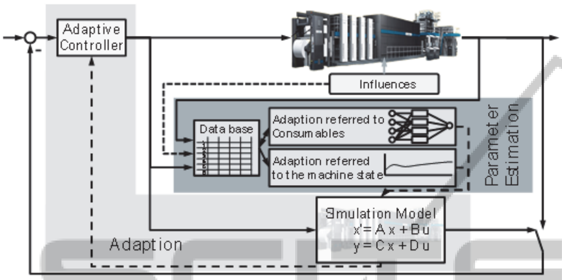

Figure 2: Model based control with parameter adaption.

For this, the main influences as well as the machine settings and the machine outputs are recorded and compressed to key figures. If a production is finished, model parameters can be calculated also, which would have enabled a high simulation quality in this past production run. Therefore parameter identification algorithms are used. These parameters and the influences build up one dataset for this machine and will be stored in a data base.

The datasets can be calculated only after a production. To know the best fitting parameters before the production it is necessary to determine them at production start.

For this a statistical adaption to the machine conditions is implemented. To consider varying influences machine-learning algorithms are used, which finds out the optimal simulation model parameters according to the consumables or the production conditions.

The model accuracy is higher than an initial parametrisized model. So the machine reaches its desired quality level sooner and improves the resource efficiency.

3.1.1 Real Printing Machine

The printing machine includes four printing units for each colour. Each unit consists of rollers, which are mechanically linked via friction to the previous and next roller, excluding the ink fountain rolle The number of rollers is necessary to transport and homogenise the ink film. The ink, stored in the ink supply, will be transported to the next roller over a gap. The size of the gap determines a minimum zone opening to transfer ink onto the next rollers. The separation between coloured and not coloured areas occurs on the plate roller, whose surface has different properties based on the image (Wang, 1984). On the non-coloured areas additional water is used in the offset printing process. Therefore a water supply is integrated in the printing unit.
r, which is driven separately. This is shown in figure 3.

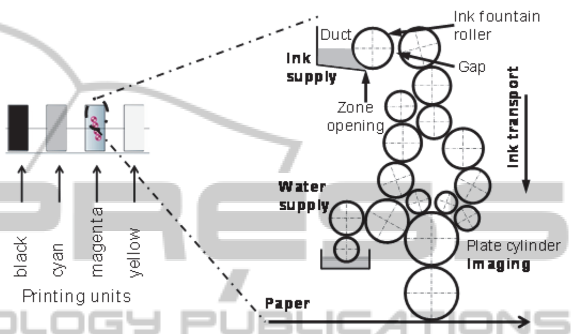

Figure 3: Schematic of a printing unit.

3.1.2 Simulation Model

Each touching point between two rollers is called nip. The mathematical description for the ink flow between two nips is a first order differential equation (Kipphan, 2002). For one zone there exist up to 50 nips and a printing unit has up to 50 zones. So the simulation model for a single printing unit consists up to 2500 linked differential equations.

To reduce the computational complexity a single differential equation has been derived for one zone, describing the behaviour according equation 1.

$$G(s)_m = \frac{K_n}{1 + sT_n} e^{-sT_t} \qquad (1)$$

The input of the system is the zone opening multiplied with the ink fountain roller speed, the output is the optical density.

The behaviour of the system is described by the system gain K_n, the time constant T_n and the dead time T_t, which regards the delay caused by the ink transport. The dead time can be calculated via kinetic and geometric studies. The time constant can be approximated analytically. The gain consists of measureable and not measureable components and describes the static ratio between the machine settings and the optical density. The gain is affected by different influencing variables, the consumables and the machine state and can not be calculated analytic.

3.1.3 Influences and Their Clustering

There are four different sources, which may influence the machine behaviour. The consumables paper, ink and water can vary. Even consumables, which should have theoretically the same properties, can behave differently because of deviations in their production process or while storage. The machine ages also, e. g. the rubber of the rollers gets harder than new ones.

The area coverage is an example of the influences of the production properties. It is the ratio between the coloured to the whole area of a sheet in percent for one zone. If the area coverage is high, the zone behaves agilely. Otherwise, when the area coverage is small, the zone behaves inertly. So the parameters of the printing job have a prevailing influence. The last types are environmental parameters. The humidity in the printing room for example changes the absorbtion rate of the water on the rollers, which results in a changing optical impress and density.

3.1.4 Adaptive Controller

When the model will be adapted to the current machine state, the controller also should be adapted. A common way is using the model's parameter according empirical methods like Chien/Hrones/Reswick or Ziegler/Nichols. For the printing process, the method of Chien/Hrones/Reswick was chosen because of its robustness and simple implementation (Aström et al., 2004).

The controller is set only once before the printing machine starts. If the controller would be tuned permanently this could cause instability. The changes of the machine characteristics during run up are small enough to be neglected.

Like mentioned before each zone has two inputs, namely the zone valve opening and the speed of the ink fountain roller. Both values affect the optical density independently from each other. It is important to recognise that the zone valve opening only influences one zone, but the ink fountain roller speed impacts all zones. Hence a conventional state space controller can not be applied. To get a linear control system, both values must be combined to a virtual machine setting, which can be controlled by a standard PI-controller. The virtual figure is the product of the ink fountain roller speed and the zone opening, corrected by the zone offset. The black line in figure 4 shows the linear controller output, which can be achived through a high ink fountain roller speed and a low zone opening or vise versa.

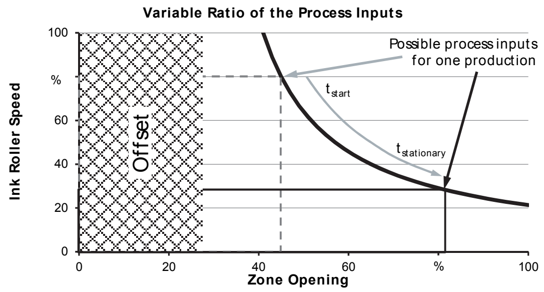

Figure 4: Variable ratio between ink fountain roller speed and zone opening.

At the production start (t_{start}) a higher ink roller speed improves the process dynamic. For a stable process control a higher zone opening has advantages ($t_{stationary}$). During the ramp up the ratio between zone opening and ink roller speed changes for high process dynamics as well as stable production.

3.2 Higher Simulation Quality by Analytic Data Mining

In this section it is described how the values of the minimum zone valve opening can be calculated from the data of the former lots. The valves of each zone needs to be opened by an offset, otherwise no colour is transferred into the printing unit because of a gap between the ink fountain roller and the following roller (see figure 5). The offset directly affects the output of the model. When the offset is high then the model calculates that only little ink can flow into the printing unit and the optical density becomes low and vice versa.

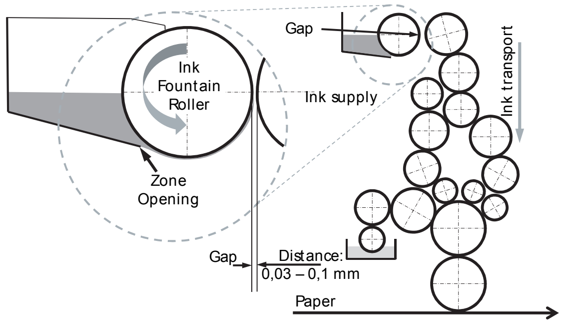

Figure 5: Physical explanation of the offset.

The distance is initial set to 0.08 mm; in reality a range of 0.03 till 0.10 mm could be measured. Reasons can be aging or pollution of the mechanical parts. The gap is implemented to control the ink roller speed independent from the other rollers without any friction. Lower zone openings do not affect the printing process. This offset makes the simulation model non-linear and needs to be considered adequate. Otherwise the model quality would be too low for the simulation (Eberhard, 2006). This can be done manually, which is very time consuming. Furthermore the production has to be stopped for at least three hours to clean and measure the zone openings. So a method has been developed to identify the offset by analysing existing machine data from the prior production runs.

When the optical density has settled then the zone opening is nearly constant. A higher zone opening takes more ink on the paper. The amount of ink can be described via the parameter area coverage. The higher the area coverage is the more ink is needed and the higher the zone opening is. There exists a nearly linear link between the area coverage and the amount of ink on the paper, shown in figure 6. For each production ID there is a pair of area coverage and stationary zone opening.

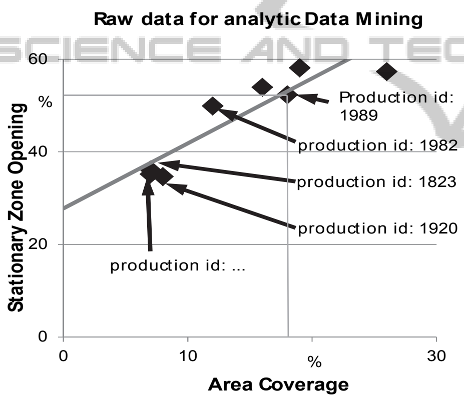

Figure 6: Zone opening compared with area coverage.

For example the production with the ID 1989 has an area coverage of 18 % and a zone opening of 52 %.

Figure 7 illustrates this relation for many productions of a real printing machine. Each dot represents one production run of a specified zone. Using numerical methods a best-fit-line can be generated. When the area coverage is 0% then no ink is needed. This set point is equal to the offset, where no colour is transfered into the printing unit and on the paper.

In practical operation there are also many operating points, which do not match exactly the line. To improve the analyses, a 2-step-filter-method is used. Therefore a first analysis determines the most probable operating points. A range of tolerance is definied on this. Only points in this range are used for the calculation of the best fit line.

According to figure 8 an offset of 18 percent can be estimated.

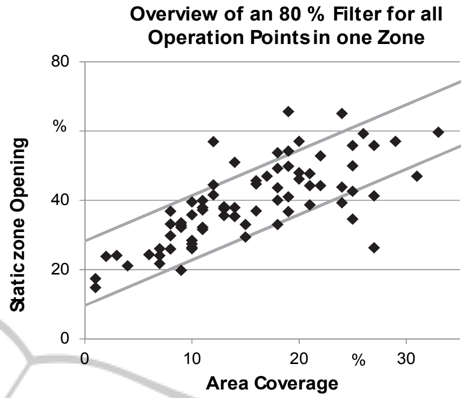

Figure 7: Analytical determination of the zone offset.

This method allows determining the actual offset value, considering dirt and mechanical imperfections without direct measurements. Figure 8 shows the comparison between the calculated and the measured values. The offsets of all 39 zones of the printing unit cyan are drawn.

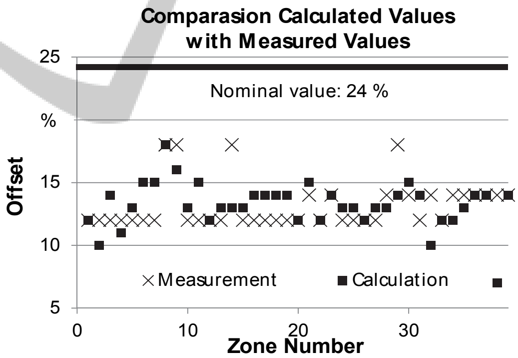

Figure 8: Calculated offsets compared with measurements.

The nominal value for the zone offset is 24 %. The calculated offsets are in a range between 7 and 18 %, the measurements are between 12 and 18 % and so the accuracy is much better than using the nominal values. Despites the huge variability of the real offsets, it is possible to build up an accurate simulation model without separate measurements.

It has already been shown, that this method improves the model quality and so increases the performance of the simulation model.

It needs to be considered that the information about the offset is just valid as long as no maintenance is performed or changes in the mechanics appear. Otherwise the data about the lots becomes obsolete and new data must get collected to get right offset values to consider the machine state.

3.3 Parameter Identification by Machine Learning Methods

Besides the machine state the consumables and the process conditions affect the process behaviour. The simplified simulation model uses a differential equation to calculate the time behaviour to calculate the optical density.

3.3.1 Physical Background

The transfer function of the simulation model can be characterized according equation 1. The model parameter K_n can vary corresponding to the physical variable ink efficiency. This variable is used to calculate the optical density at specific machine settings. It is possible to calculate the ink efficiency on the basis of the measurements afterwards each production, but not before. An analytic determination is also not possible, because there are too many crossactions between process, paper and ink and moreover the physical and chemical processes have not yet been identified. This means finite element analyses are not possible.

Because of this reasons, a multilayer perceptron (MLP) is used to estimate the ink efficiency on the basis of the influence parameters (Hintz, 2003). An MLP is a kind of Neural Network, which consists of one input and one output layer and several hidden layers. Each hidden layer is built of neurons (Bayer et al., 2011); (Beuschel, 2000).

3.3.2 Usage of an MLP to Calculate the Ink Efficiency

The MLP reproduces the relationship between the influence parameters and the optimal model parameters. For this, at first a training period must be completed successfully (Zell, 1994); (Faridi, 2011). A supervised learning algorithm, that enables a fast adaption of the network parameters, requires a training data set, which includes the input parameters and the corresponding outputs, namely the parameter ink efficiency. This parameter is necessary to calculate the model parameter K_n in equation 1. The training set is calculated according former production runs. All measurements will be analysed and compressed to key figures for the input variables. The input parameters are the influence variables like the proberties of the consumables paper, ink and water, the process conditions like the temperature and humidity and other physical characteristics. The corresponding output is the effective ink efficieny, which can be calculated via parameter identification algorithms. This is only possible with completed production runs. The training period is finished when the net output is near the desired output. This means, that the net behaviour is similar to the training sets and thereby to the machine characteristics.

To use the trained MLP it is necessary to use the influence parameter of the next production run as net input. At the start of the production all influence parameters have to be measured. With these inputs the MLP can estimate the most probable ink efficiency for the next production. This enables the computation of the model parameter K_n for an optimal simulation accuracy of the simulation model. This enables a parameter adaption of the model and the controller before the start and without a closed loop control. It is called cognitive parameter adaption, because only influence variables are used and combined in a new way.

3.3.3 Topology of the Neural Network

For this application an MLP net was selected because it is particularly suitable for handling many inputs. The input and the output data are linearly normalized due to their physical range of values. The output neuron has a linear activation function so that the ink efficiency can be any value between 0.5 and 2.5. All other neurons obtain a sigmoid activation function. The number of inputs and output neurons are held constant. The actual structure of the Neural Network is not predefined.

3.3.4 Topology Optimisation of the Neural Network

To find the optimal network structure, several networks with different structures are trained with the same training data. The networks vary in the number of hidden layers and in the total number of neurons. At the end of the training phase the performance of each network will be evaluated automatically using a reference data set. The network with the least error is assumed to have the best structure and the best ability to generalise, so this will be used for further calculation of the ink efficiency.

3.3.5 Workflow

Before the production starts, the simulation model sends a request to the Neural Network to deliver the ink efficiency. The network gathers all input values, calculates the ink efficiency and sends it to the simulation model. This step takes up to 20 seconds.

The training and the optimisation of the network take up to 30 hours. This is not time critical because the network gets trained only once a month on a separate computer. If a new production starts while training, the old network will be used to calculate the ink efficiency. This means that the training and the usage is completely separated.

4 RESULTS

4.1 Improvement of the Machine Behaviour using a Model based Controller

Until now no dead times are considered in the controller design. The same can be stated for many other important influences. So the controller is designed slowly to avoid unstable behaviour. This results in a slow system dynamic according to figure 1. The desired optical density of 1.6 is reached at t = 500 seconds and so the machine produces insufficient quality for more than 300 seconds.

Figure 9 shows the rising of the optical density using the model based adapted controller. These values can be compared with figure 1, the controller and system behaviour is simulated offline.

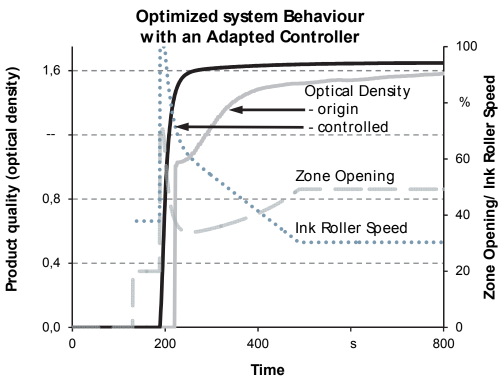

Figure 9: System dynamic with a model based controller.

At t= 190 seconds the ink roller speed is set to 100 % and the zone opening get up to 70 % for some seconds and get down after that, so a dynamic ramp up is possible. Also the variable ratio between zone opening and roller speed is shown. It can be seen easily that the machine, which starts at the same time, just needs 30 seconds to reach good quality. This means that in this case the efficiency was increased by the factor of 10 in the simulation. It can be seen that the density does not overshoot.

4.2 Quality of the Model Adaption

4.2.1 Determining the Zone Offset

The information, which is currently used for the model, can also be helpful for other purposes. It could already be proven that the offset in the zone valve opening has a drift from one side to another without any visible reasons. This information was used to demonstrate that an overhaul needs to be done, which includes cleaning and a mechanical setup of the zone offsets.

4.2.1 Neural Identification of the Model Parameter

The Neural Network determines variables, which cannot be calculated before production start. It needs to be considered that a Neural Network needs as many training data sets as possible to cover all possible variations of the input parameters. The training sets have to be evenly spread over all parameters. Furthermore it is also necessary to substitute old data by new one. This is especially caused by the aging of the mechanical parts and due to deposits. Additionally several filters are applied for the training data, which increases the accuracy of the data and enables a well-designed network.

5 OUTLOOK AND NEXT STEPS

Most experiments are done on a test printing machine. Currently it is being integrated into a real production system. Therefore the model and the controller have been extended. Furthermore the Neural Network needs to be optimized so that its training takes less time. Input parameter with small effects skipped.

Furthermore the effect of the Neural Network on the simulation quality has to be determined. Therefore the real control behaviour with and without the parameter adaption must be compared.

6 CONCLUSIONS

It is state of the art to apply conventional control theory for production machines. More powerful tools like self-learning systems are rejected because of their non-deterministic behaviour.

To improve the resource efficiency of a printing machine the capacity of these systems are needed. A combination of the mathematical deterministic of analytic controllers with an advanced self-learning system was developed for a printing machine.

For this machine a transfer function model was designed which describes the principal behaviour. To identify the model parameter before the production start, diverse devices and information about the consumables and the environmental conditions are used. All influences, whose correlation can be described analytically, are also calculated in that way. Influences with unknown mode of action are regarded with a Neural Network. Therefore the most important impacts are measured, conditioned and fed to the network. So it is possible to predict the machine's behaviour under varying operation conditions with unknown effects. The simulation model and the controller are turned according the adapted parameter to guarantee a stable and dynamic production. This enables higher product quality and efficiency.

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REFERENCES

Aström, K. J., Hägglund, T., 2004. Revisiting the Ziegler–Nichols step response method for PID control.

Bayer, J., Osendorfer, C., Smagt, P., 2011: Learning Sequence Neighbourhood Metrics. Technical University Munich.

Beuschel, M., 2000. Neuronale Netze zur Diagnose und Tilgung von Drehmomentschwingungen am Verbrennungsmotor, Technical University Munich.

Eberhard, M., 2006. Optimisation of Filtration by Application of Data Mining Methods, Dissertation, Technical University Munich.

Faridi, A.; Golian, A., 2011: Use of neural network models to estimate early egg production in broiler breeder hens through dietary nutrient intake. In: *Poultry Science*.

Govindhasamy, J. J.; McLoone, S. F.; Irwin, George W.; French, J.; Doyle, R. P., 2005: Neural modelling, control and optimisation of an industrial grinding process. In: *Control Engineering Practice 13*.

Guanyuz, Zhou (2012): Online incremental feature Learning with denoising autoencoders. *International Conference on Artificial Intelligence and Statistic*, 2012.

Hafner, R. 2009: Dateneffiziente selbstlernende neuronale Regler. University Osnabrück.

Hintz, Christian, 2003: Identifikation nichtlinearer mechatronischer Systeme mit strukturierten rekurrenten Netzen. Dissertation. Technical University München.

Huang, S.H; Hong-Chao Z., 1994: Artificial neural networks in manufacturing: concepts, applications, and perspectives. *IEEE Trans. Comp., Packag., Manufact. Technologies.*

Kipphan, H., 2002. Handbuch der Printmedien, Springer Verlag, Berlin.

Moon, P.; et al. , 2008. Ink-jet printing process modeling using neural networks. *International Electronics Manufacturing Technology Conference*.

Rangwala, S. Dornfeld, D. A., 1989. Learning and optimization of machining operations using computing abilities of neural networks, *IEEE Transactions on Systems, Man, and Cybernetics*.

Ramesh. R., Mannan M.A., Poo A.N., 2002. Support vector machines model for Classification of Thermal Error in Machine Tools, in: *The International Journal of Advanced Manufacturing Technology*.

Rajagopalan, Ramesh; Rajagopalan, Purnima, 1996. Applications of Neural Network in Manufacturing. *International Conference on System Sciences*.

Suzuki, K, 2011. Artificial Neural Networks - Industrial and Control Engineering Applications.

Wang, D., 1984. An investigation of the applicacability of Walker and Fetsko ink transfer equation, Rochester, New York.

Rae, T.A; et al, 1996. The application of neural Networks to induction machine control. *Proceedings of IEEE*.

Zell, A., 1994. Simulation neuronaler Netze, Oldenburg Verlag, München.