Neural Networks in Production Control

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Abstract: In order to keep up with the fast changing requirements of today’s global markets, production planning and control systems need a continuous advancement. In recent years, methods from the field of artificial intelligence, such as biologically inspired algorithms, software agents or artificial neural networks, have proven their innovation potential in tasks related to production planning and control. However, the practical application is often difficult due to the lack of experience with these new approaches. This paper deals with the use of artificial neural networks as control methods in a shop floor environment. It provides an evaluation of three common network architectures based on material flow simulations with a generic shop floor model.

Key-Words: Production control, artificial intelligence, artificial neural networks, shop floor production, material flow simulation, radial basis function network, feed-forward network, cascade correlation architecture

1 Introduction

Today, companies face fast and dynamically changing markets with a high percentage of multi-variant and customized products. The corresponding short product life cycles lead to complex material flows and increasing requirements on the production processes [1].

In order to cope with these problems, the related production planning and control systems need a continuous advancement concerning control strategies and their technical implementation. In research, methods from the field of artificial intelligence such as software agents, biologically-inspired algorithms and artificial neural networks have shown their potential in control related tasks. Especially in the case of neural networks, the transfer into the practical application often fails due to the lack of experience concerning the conception and implementation of such innovative systems.

This paper contributes to the development of new production control approaches basing on neural networks by evaluating three common network architectures in a shop floor environment. This production form is characterized by the manufacturing of highly customized products in small series, single pieces or prototypes [1].

Therefore, the above mentioned problems concerning the complexity and dynamic of production processes and material flows are particularly applicable. The comparative evaluation of the neural network types bases on simulations with a generic shop floor model applying the adaptive relocation control (arc) described in [2].

At this, the paper is structured as follows. Section 2 first introduces artificial neural networks in general, followed by a short description of the three evaluated network types. Section 3 deals with the production form shop floor, before section 4 describes the generic model for the experimental validation. The paper closes with the results of the experimental validation in section 5 and a summary/outlook in section 6.

2 Artificial neural networks

Artificial neural networks are mathematical models of neural systems in nature [3]. Similar to the example, neural networks consist of processing units, called neurons. Within the network, the neurons are structured in layers depending on their function and connected via weighted links (Fig.1). At this, the input and the output layer are responsible for the interaction with the environment. Correspondingly, every neural network has at least these two layers [4]. Subject to the purpose and type of the neural network, an unlimited number of so called hidden layers between the input and the output are possible.

Within the network, every neuron computes its activation using a so called activation function that processes all values arriving via the connected links. In a second step, the activation is compared to a
threshold. In the case, the threshold is exceeded, an output function calculates the output of the neuron. It is also possible, to forward the activation directly by using the identity function for the output.

In general, neural networks come into operation to deal with complex mathematical coherences which are either not exactly describable or completely unknown [2] [5].

Fig.1: Example of an artificial neural network

In this case, the neural network acts as a kind of black box. Besides this functionality, neural networks feature a fast data processing and a comparatively small modelling effort. Further, neural networks are able to learn from examples or experience gained through operation [3]. In general, three different learning paradigms are possible.

Supervised learning denotes learning from examples of input and output pairs. A repeated presentation of these pairs leads to a continuous adaption of the link weights according to the training error [6]. Reinforcement learning follows a quite similar approach. The network repeatedly receives input data. According to the computed output, a feedback concerning the correctness is given. Finally, unsupervised learning describes a learning procedure without any feedback. At this, the neural network tries to approximate possible coherences within the input data autonomously [3].

To avoid a possible memorizing of the learned data (called overfitting), every learning cycle ends with the presentation of an unknown dataset for validation purposes. This proceeding is common for all three learning procedures. Besides the avoidance of the overfitting effect, the validation with extra data sets ensures the generalization of the trained network. At this, generalization denotes the ability of a neural network to compute a correct output for completely unknown input data.

In general, neural networks can be distinguished by their area of application. Depending on their purpose, the topology and possible learning procedures can vary [4]. For example, recurrent or partially recurrent networks are predestined for prediction purposes [3], while classification is a typical application area for self-organizing maps (SOMs) [7].

This paper evaluates the learning and functional behavior of three common network types in a production control application. The following subsections give a short introduction to each considered network type.

2.1 Feed-forward Networks
The feed-forward architecture is one of the most basic and therefore common topologies for neural networks [6]. Within a feed-forward network, all connections between neurons direct from the inputs to the outputs, without any loops (Fig.1) [3].

Besides the sequential connection from layer \( n \) to the following layer \( n+1 \), so called shortcuts are possible. These connections can skip one or more layers and connect layers that are not directly adjacent.

Due to their comparatively simple topology, feed-forward networks are easy to construct and offer a fast learning process. Their all-round properties make them applicable in manifold application areas such as production control [8] or signal diagnosis.

2.2 Cascade Correlation Networks
The cascade correlation (cascor) networks are an example for network types, whose structure follows their learning behavior [9]. An initial cascade correlation network only contains a number of directly connected input and output neurons, depending on the problem to learn. Before the original cascor algorithm starts, the initial network is trained using a common learning technique for feed-forward networks, like Quickpropagation, for example. If the network fails to reach a desired error level, the cascor algorithm comes into operation. During this special training process, the learning algorithm gradually integrates new hidden units into the network [10].

At this, every learning cycle is called a cascade and passes through the following steps. First, the learning algorithm inserts one or more candidate neurons into the existing network. Every candidate neuron has connections only to the input neurons and to possible hidden neurons, not to the outputs. In the following, the candidate neurons train to maximize the correlation between their activation and the residual error on the current training set [9]. The neuron with the maximum correlation is integrated into the network and connected to the outputs using new links with random weights. The
weights of the already existing links to the former candidate are frozen. Finally, the random links between the outputs and the new neuron pass an additional training process, using a common strategy again. Fig. 2 shows an example cascor network after two iterations. At this, the boxed connections are frozen, the ones with an x are subject to the training process. Further, the vertical lines sum up the activation for the neurons [9].

Fig. 2: Cascor network after two iterations [9]

A repetition of the whole proceeding takes place, if the new network again fails the desired error level. As every cascade changes the topology, cascade correlation networks are called constructive networks [11].

Possible areas of application for cascade correlation networks are prediction purposes or the processing of structured data or pattern recognition [10].

2.3 Radial Basis Function Networks
Radial basis function (RBF) networks are three layered networks with a feed-forward architecture. Within the network, the input layer forwards the input value via links with a fixed weight of +1. The neurons of the hidden layer have individual radially symmetric activation functions, such as the Gaussian function [12]. From a mathematic point of view, these radially symmetric functions act as a kind of basic functions (supporting point) for the approximation of multidimensional functions.

The learning of RBF networks basically consists of two steps. The first is a nonlinear adaption of the hidden layer, the second is a linear optimization of the output layer. At this, the first step comprises the selection of appropriate supporting points for the applied Gaussian functions. This selection can take place randomly or use a supervised procedure. In the latter case, the supporting points normally shift to areas within the input space, which have a sufficient representation in the training data [12]. It is also possible, to distribute the supporting points equally over the solution space of the function.

Radial basis function networks are, for example, applicable in face recognition or fault detection of circuits [13].

3 Shop floor production
The comparatively evaluation of the three neural network types introduced above takes place in a shop floor environment. Shop floor production as an organizational form is characterized by the manufacturing of customized products in relatively small quantities [14]. The production of customer-oriented prototypes, single pieces and small series complicates the material flows and the related production processes.

The layout of a shop floor follows the functionality of the resources. Correspondingly, the production facility is typically arranged in different specialized workshops, such as a sawmill or a turnery [2] (Fig. 3). At this, each workshop contains a number of technically different machines. This implicates varying setup and processing times for each work piece.

Fig. 3: Example layout of a shop floor [15]

In general, the work pieces have a slight lot size and can pass the workshops in any order. Further, varying machining sequences are common, due to the high grade of customization [15].

4 Experimental Settings
The experiments base on simulation runs with a generic shop floor model using the software Plant Simulation®. The model comprises 12 workstations in 5 workshops (Fig. 4). Each simulation run lasts
30 days with a startup and phasing-out period of 2.5 days each. During the simulation, 7 work piece types in homogeneous lots with 1-4 pieces each run through the model. The total amount of orders is around 3150. Further, the 7 work piece types are equally distributed within the order data.

The work piece types vary in setup and processing times, depending on the current machine. In general, the work piece types 1, 2, 6 and 7 run successively through every workshop, while the types 3, 4 and 5 can have varying machining sequences. The results are possible backflows between the workshops 1, 2 and 3.

The redistribution of work pieces between the workshops follows priority rules regarding the inventory level of the involved machines. As control methods, neural networks with a feed-forward architecture come into operation. At this, the general approach is inventory based, following Scholz-Reiter and Hamann [8]. If a work piece leaves a workshop, a specialized neural control network considers the setup and processing times of the current work piece for all machines in the subsequent workshop. Further, the actual inventory level of each eligible machine is taken into account.

To ensure the generalization of the redistribution decision, all three processed values are correlated with the desired inventory levels for every machine. These are 42 minutes for the machines of the first and fourth workshop, 63 minutes for the second and 84 minutes for the third workshop. To reduce the training and operation effort for the neural control, every work piece type has an own specialized neural control network.

For the experimental simulation runs, the expert network for the distribution of work piece type 3 between the workshops 2 and 3 is replaced by the examined optional network. This decision results from previous test runs, where work piece 3 obtained the longest lead time of all 7 types. The redistribution between the workshops 2 and 3 is interesting, because workshop 3 offers the most machines to choose between.

The experiments take place in a two-stage proceeding. First, several variations of every architecture compete with each other to determine the best network for the overall evaluation. This second passage comprises the best network of the three considered architectures, respectively. Within the first stage, the candidate networks vary with regard to the number of hidden layers and/or neurons, as well as with regard to the applied training method and the corresponding parameters.

The feed-forward networks should now serve as an example for this proceeding. The first stage evaluation of this network type comprises 4 variations. 2 networks with 1 hidden layer containing 10 or 50 neurons (12:10:4 and 12:50:4 topology) and 2 networks with 2 hidden layers of 20 and 50 neurons each (12:20:20:4 and 12:50:50:4).

At this, the size of the input and output layer depends on the position of the network in the material flow. As mentioned before, the network serves as relocation controller for work piece type 3 between workshop 2 and 3. Therefore, the network has 4 machines to choose between (M_{13} – M_{43}). With 3 parameters to consider per machine, the network needs 12 input and 4 output neurons in total.

The training phase comprises experiments with 4 different learning algorithms; Quickpropagation, Backpropagation with momentum term as well as the Hebb and Delta learning rule (for details concerning the algorithms, cf. [3]). The training phase comprises experiments with 4 different learning algorithms; Quickpropagation, Backpropagation with momentum term as well as the Hebb and Delta learning rule (for details concerning the algorithms, cf. [3]).
results, measured in form of the medium square error, show a performance lead for the network with the 12:50:4 topology. Therefore, this configuration takes part in the second stage of the evaluation.

The proceeding for the remaining 2 network types is similar whereby the main parameter for the cascade correlation networks was the number of permitted candidate units per cascade.

5 Results
The evaluation of the results bases on the logistic parameters average lead time (ALT), adherence to delivery dates as well as on the average distribution of the lead time ($\sigma_{LD}$). As mentioned above, all measurements only consider work piece type 3.

At this, for the adherence to due dates, two tolerance ranges were defined. The first one comprises a period of 30% of the average lead time for work piece 3 (T30). The second one comprises 15% of the average lead time (T15). Both tolerance ranges are centered on the desired due date.

Table 1 shows the results of all three network types in comparison. The feed-forward network with the 12:50:4 architecture (FF_1-50) reaches an adherence for delivery dates of 86.39% within the 30% tolerance. In contrast, only 57.07% of the work pieces are on time regarding the tolerance of 15% around the due date. The average lead time amounts approximately 7 hours and 54 minutes (format hours:minutes:seconds) while the distribution of the average lead time is around 1 hour and 40 minutes.

<table>
<thead>
<tr>
<th>Param.</th>
<th>T30</th>
<th>T15</th>
<th>ALT</th>
<th>$\sigma_{LD}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>FF_1-50</td>
<td>86.39</td>
<td>57.07</td>
<td>7:54:13</td>
<td>1:39:09</td>
</tr>
<tr>
<td>RBF_1-05</td>
<td>80.96</td>
<td>43.77</td>
<td>7:18:32</td>
<td>1:43:37</td>
</tr>
<tr>
<td>CCLA_8C</td>
<td>96.20</td>
<td>76.63</td>
<td>6:55:20</td>
<td>59:39:00</td>
</tr>
</tbody>
</table>

The radial basis function network (12:5:4 topology) shows a worse performance. Only 80.96% of the work pieces reach tolerance period 1, less than the half (43.77) leave the shop floor within tolerance period 2.

The cascade correlation network with 8 complete cascades (12:8:4) shows better results for all criteria. However, this network causes some discrepancies regarding the number of finished orders. While the original control networks used by Scholz-Reiter and Hamann, as well as the actual tested feed-forward and RBF networks manage around 3200 work pieces in total, the cascor networks only finishes around 1900. Several experiments with the cascor network lead to the conclusion that the reaction rate of this network type in interaction with the applied simulation software (JNNS) possibly causes the differences between the network types.

Altogether, the learning behavior and the experimental results of the three network types show a general suitability for the application in production control related tasks. With regard to the measured performance, the feed-forward networks obtain the best results, closely followed by the radial basis function networks. The cascade correlation networks also show good results, but cause problems regarding the technical application.

6 Summary/Outlook
This paper evaluates three types of artificial neural networks concerning their suitability for control related tasks in a shop floor environment. In a two-staged proceeding, different topologies differing in the number of layers and neurons as well as the applied learning technologies, compete with each other. The final results show advantages for the feed-forward architecture, but also certify a general suitability for the other two network types.

Future research should focus on the examination of other network types and the associated learning techniques. Further, the behavior in the long-term operation and the maintenance properties are from interest. In a final step, experiments in a real production facility could validate the simulation results and give valuable feedback concerning the practical application of artificial neural networks in production control.

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References:


