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AN INVENTORY AND CAPACITY-ORIENTED PRODUCTION CONTROL CONCEPT FOR THE SHOP FLOOR BASED ON ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The constantly growing demand for customized and innovative products results in highly complex production processes. The corresponding large workload of the production planning and control systems strengthens the interest in flexible, adaptive and intelligent approaches for both manufacturing systems and the related production control. Methods from the field of artificial intelligence, such as software agents or artificial neural networks, have proven their applicability in this field. This paper presents a production control concept based on artificial neural networks for the inventory and capacity-oriented control of a shop floor. An example demonstrates the overall concept as well as the implementation and performance of the proposed control system

KEYWORDS

Production Control, Shop Floor, Capacity, Inventory, Artificial Neural Networks

1. INTRODUCTION

The customer-oriented production of multi-variant products with short production cycles plays an important role in today`s market (Schäfer et al., 2004). This results in complex and dynamic production processes, which are difficult to handle for established production planning and control systems (Barata & Camarinha-Matos, 2005). Due to the orientation to small series, single pieces and prototypes, shop floor productions have a particular demand for a continuous advancement of production control strategies and techniques.

In this context, methods from the field of artificial intelligence, such as bio-inspired algorithms (Scholz-Reiter et al., 2008), software agents (Scholz-Reiter & Höhns, 2003) and artificial neural networks (Rippel et al., 2010) (Scholz-Reiter et al., 2010) have proven their applicability in production related tasks. At this, the application ranges from machine control (Kwan & Lewis, 2000) over prediction purposes (Natarajan et al., 2006) to the determination of suitable operational policies (Yildirim et al., 2006) (Chryssolouris et al., 1991).

This paper introduces a production control concept for the combined control of inventory levels and capacity utilization within a shop floor production. In this concept, artificial neural networks act as capacity and inventory controller in cascaded control loops.

The structure of the paper is as follows: The next section gives a short overview of artificial neural networks in general. Section 3 introduces the organizational form shop floor production and the generic shop floor model that underlies the experiments. Section 4 describes the overall control concept and the neural controllers it uses. An experimental validation of the concept by means of the previously described model follows in section 5. The paper closes with a conclusion basing on the obtained results and gives an outlook on future research.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks represent mathematical imitations of neural systems found in nature (Dreyfus, 2005). They consist of artificial neurons, also called nodes, and weighted links, also known as edges (Steeb, 2008). A typical neural network consists of three layers, an input layer, one or more hidden layers and an output layer (Haykin, 2008). At this point, the number of hidden layers depends on the type of network (Steeb, 2008). Figure-1 depicts a schematic view of an artificial neuron.

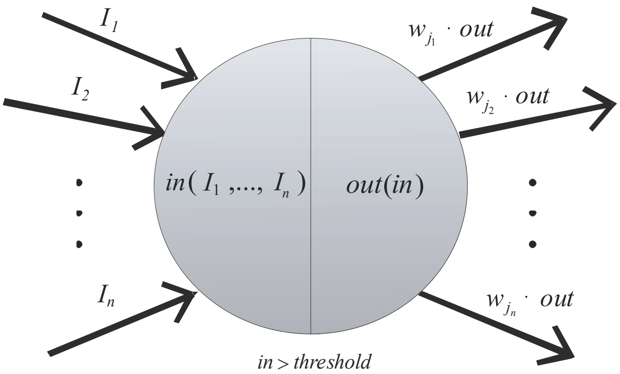

Figure - 1 Schematic view of an artificial neuron (Rippel et al., 2010)

Within a neural network, the artificial neurons act as data processing units. They process input data, coming from other neurons or the environment, and forward the calculated results. Therefore, neural networks offer a fast and parallel data processing (Dreyfus, 2005).

Further advantages of neural networks are a comparatively small modelling effort and the ability to learn from experience (Scholz-Reiter & Höhns, 2003). This learning ability empowers neural networks to approximate complex mathematical coherences, which are not exactly describable or may be even unknown (Rippel et al., 2010). In this case, the networks act as a kind of black-box.

The learning process can take place in three different ways. Supervised Learning is applicable, if data in form of matching input output pairs exist (Chaturvedi, 2008). Their presentation to the network triggers an adjustment of the internal connections in a way that every input generates the corresponding output. Reinforcement learning follows a similar approach. At this point, the network receives input and a feedback concerning the correctness of the result (Haykin, 2008). The exact desired output is not presented. Finally, Unsupervised or Self-organized Learning denotes a learning process without assistance. The neural network receives only input data and tries to approximate possible coherences within the presented pattern autonomously (Kohonen, 2001).

In all of the three cases, the success of the learning procedure is verified by presenting an additional set of validation data. This avoids a merely memorising of the initial training data (Haykin, 2008).

3. SHOP FLOOR PRODUCTION

3.1 SHOP FLOOR PRINCIPLE

Shop floor production is a very dynamic and complex form of production. The manufacturing of prototypes, single pieces and small series results in a high degree of customization (Rippel et al., 2010). The production facility is organisationally divided into specialised workshops, such as a turnery, a sawmill and so on (Figure-2). Within the shop floor, work pieces can pass machines and workshops in any order (Slack et al., 2007). At this point, the machining sequence depends on the technical specifications of both the work piece and available workstations or machines (Rippel et al., 2010). Often, processing steps have a variable order or are optional.

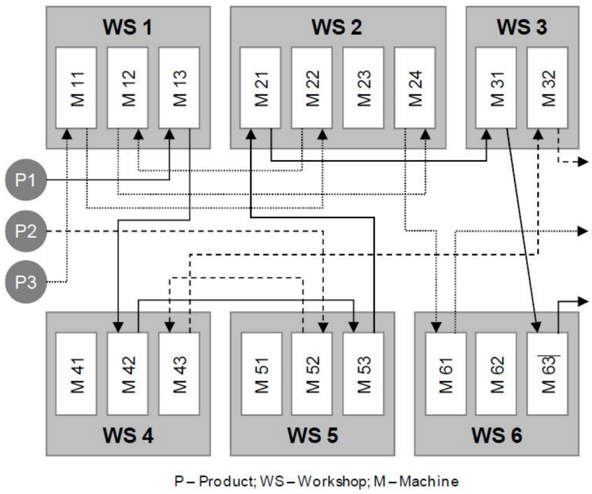

Figure – 2 Shop floor organization (Scholz-Reiter et al., 2011) (Pfohl, 2010)

The resulting flexibility leads to complex material flows and highly dynamic production processes. As a result, scheduling within a shop floor is quite difficult and often referred to as the job shop or shop floor scheduling problem (Chen et al., 2008). The complexity of production planning and control systems in this field is correspondingly high.

3.2 GENERIC SHOP FLOOR MODEL

The evaluation of the control approach introduced in this paper takes place by means of a generic shop floor model. The model consists of nine technically different machines in four workshops (Figure-3). Every workshop contains an input buffer in front of the respective machines.

During the simulation period, six different types of work pieces are manufactured. At this point, all work piece types run through every workshop. To reflect the general complexity and dynamics of a shop floor, the manufacturing steps for one of the work piece types is variable. Pieces of this type can pass the production stages in varying orders, while backflows are possible in workshop 3, as a consequence of quality effects. Further, the set-up and processing times differ for every work piece and machine. This depends on technical specifications and/or the sequence the work pieces arrive in.

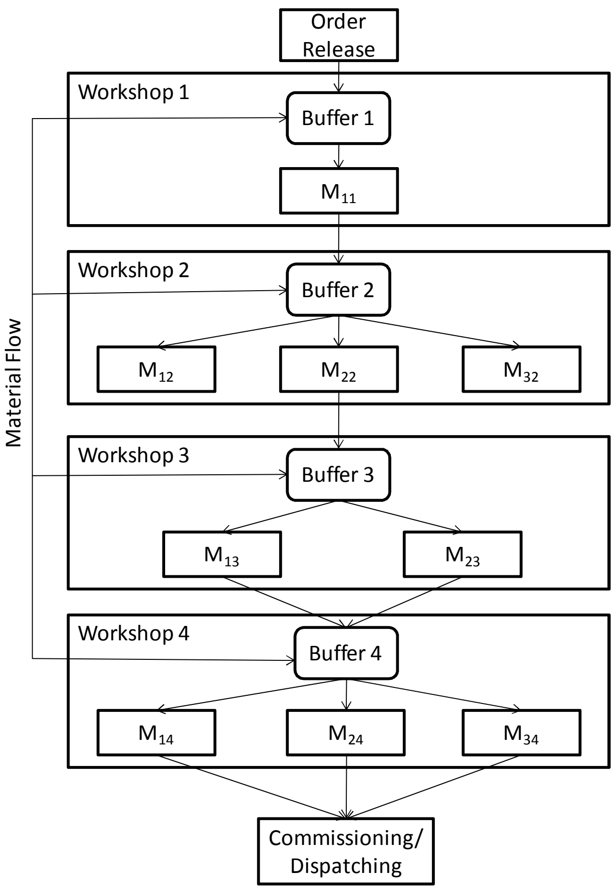

Figure – 3 Schematic view of the shop floor model

The order release takes place in front of the first workshop. The size of the homogeneous lots amounts up to five work pieces. Finally, the commissioning forms the end of the production process.

4. THE NEURAL CONTROL CONCEPT

The proposed concept focuses on combined control of inventory levels and capacity utilization. At this, the capacity utilization denotes the time slice that a machine *m* processes a work piece or is set up for processing. The calculation is as follows:

$$CU_m = PT_m + ST_m \qquad (1)$$

1. CU_m: Capacity utilization of machine *m*.
2. PT_m: Time slice, machine *m* works.
3. ST_m: Time slice, machine *m* is set up.

The inventory level bases on an average between the machine specific inventories of the considered workshop. Equation-2 defines the individual inventory calculation for every machine *m*:

$$I_m = \left(\sum_{i=1}^{k}(PT_i + ST_i)\right)_m \qquad (2)$$

1. I_m: Inventory level of machine *m*
2. PT_i: Processing time for work piece *i* on machine *m*
3. ST_i: Setup time for work piece *i* on machine *m*
4. i: Current work piece *i* on machine *m*
5. k: Number of work pieces within the buffer

Within the shop floor, every workshop is equipped with one neural control network per control variable. Together, the neural controllers form a cascaded control structure, with the capacity control as the inner and the inventory control as the outer control loop. The inventory levels are decisive for the distribution of work pieces between the different workshops. The allocation of work pieces to machines inside a workshop follows the capacity utilization.

In this context, the general control flow provides a transfer of work pieces depending on set-points for the inventory levels of workshops. Redistribution only takes place, if it does not exceed the desired limit. To avoid a standstill of individual workshops, a transfer is allowed in special cases, however. A special case occurs, when a compliance of the desired inventory would lead to a blockade in one or more workshops. Within a workshop, the capacity control assigns the work pieces waiting in the buffer to the available machines.

The neural inventory controllers have a feed-forward architecture. The precise design depends on the position of the considered workshop within the material flow. In the following, the control network of a workshop with three machines will serve as an example. The network has a 4:12:12:1 topology with four inputs, one output and two hidden layers with 12 neurons each. Figure-4 shows a schematic view of the corresponding network. Because of space reasons, a black-box replaces the detailed presentation of the hidden layers. This also refers to the approximation of possible coherences between the input and output data in a black-box manner.

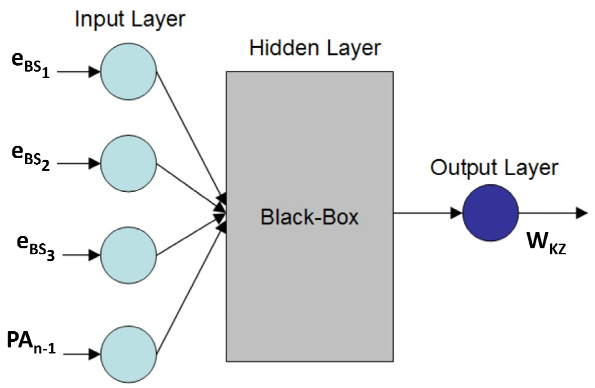

Figure – 4 Schematic view of a neural inventory network

The depicted network computes an inventory based factor (W_{KZ}), which is determining for the distribution decision. Hence, it processes the inventory deviation for the three machines as well as the number of breaks for the previous workshop in the material flow.

The deviation is defined as the quotient between the desired and the actual inventory level. The use of this quotient instead of the difference leads to a normalization of the input values for the neural networks. Further, the quotient reflects the ratio between actual and desired inventories. This simplifies the generalization of the neural networks, as absolute values always depend on closely restricted situations.

The amount of breaks denotes the time, the machines of the previous workshop are blocked. A high amount of breaks is an indication for an overload. In this case, a redistribution can take place despite a possible exceeding of the inventory limits. With regard to the example, this implies the following input variables:

1. E_{BSm}: Normalized inventory error for machine *m*

2. PA_{n-1}: Amount of breakes for previous workshop *n-1*.

The corresponding neural network for the capacity control has a 6:12:12:3 topology. It processes six input values and computes a ranking for the three available machines. At this, the machine with the highest ranking gets the respective work piece (winner-takes-it-all) for machining. Figure-5 depicts the neural capacity controller for the example workshop with three machines.

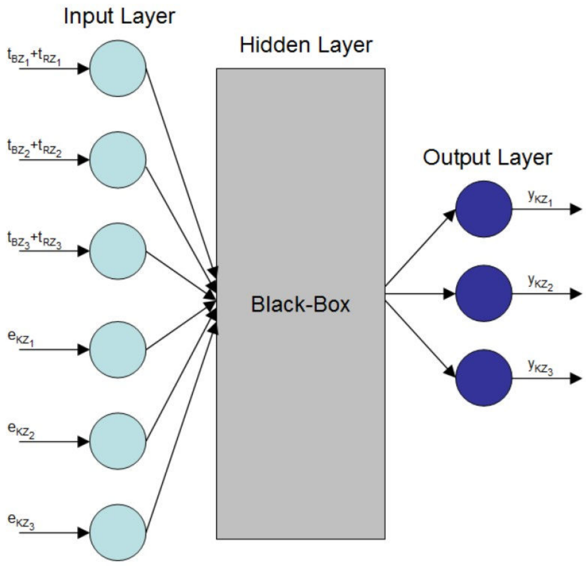

Figure – 5 Schematic view of a neural capacity network

The controller processes the following input values:

1. t_{AZn} + t_{RZn}: Setup and processing time of the regarded work piece on machine *m*

2. e_{KZm}: Current capacity utilization of machine *m*

3. Y_{KZm}: Ranking for the redistribution decision with regard to machine *m*

Both types of control networks run through a supervised learning procedure. The learning and the validation data were recorded during test runs of the shop floor model introduced in the previous section. During this runs, the control was based on simple priority rules. At this point, only redistribution decisions with the desired results found entrance in the training and validation database as input output pairs.

5. EXPERIMENTAL VALIDATION

The experimental validation comprises two simulation runs, simulating a production period of 30 days each. Within both runs, 5000 orders run through the shop floor. As mentioned in section 3.2, every order comprises a lot of 1 up to 5 pieces. Main difference between the two setups is the

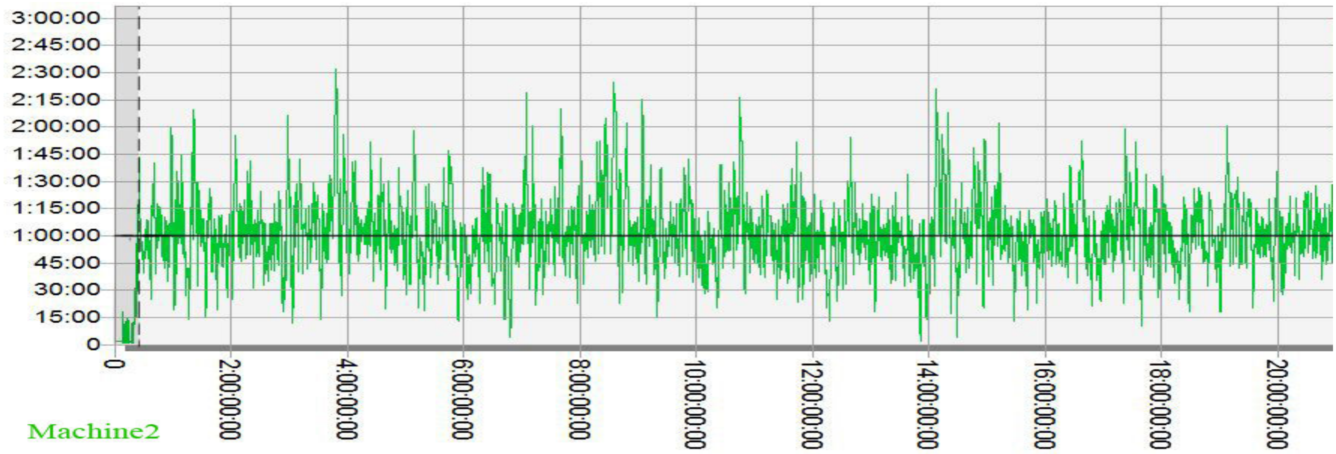

Figure – 6 Inventory course of machine 2 in workshop 2

desired inventory level. The first run bases on a general inventory limit (mentioned as set-point in section 4) of 60 minutes for every workshop of the shop floor. The second simulation works with a limit of 80 minutes.

The neural control concept affects the workshops 2, 3 and 4 excluding workshop 1, as the first production stage receives its orders directly from the order release. The following results exemplarily explain the obtained results of workshop 2 for an inventory limit of 60 minutes. This is the first workshop with a neural control within the material flow. Figure-6 depicts the inventory course of machine 2 inside the considered workshop. The remaining two machines are not depicted. The illustration covers an extract of approximately 21 days.

At this point, the first 12 hours (grey shaded) represent the initial period of the simulation. The missing nine days cover the phasing-out period of workshop 2. Further, days with a decreasing occupancy towards the end of the simulation are left out. The length of this period results from the front position of the considered workshop within the material flow. Both periods do not flow in the inventory analysis. The adjusted inventory curve shows a typically uneven course with only a few variances. The averages mostly correspond to the desired values. At this, machine 2 has an average inventory of 63 minutes, machine 1 achieves approximately 70 minutes and machine 3 is around 75 minutes. The overall deviation amounts between 3 and 16 minutes.

The capacity utilization is, in contrast to the satisfactory inventory values, insufficient (Figure-7). The utilization of the machines in workshop two ranges from 27.40% to 28.96%. The average of 27.66% constitutes the minimal value for the whole shop floor. At this point, the results extend to a maximum of 41% for workshop 3. Further, the curves for all machines belonging to this workshop show a noticeable even course with only small deviations after the transient phase.

The insufficient capacity utilization originates from two reasons: the distribution of work piece types within the job data and the physical structure of the shop floor. The work piece types are equally distributed over the job data. The even course of the utilization after the end of the transient phase is a direct consequence. Further, the physical structure

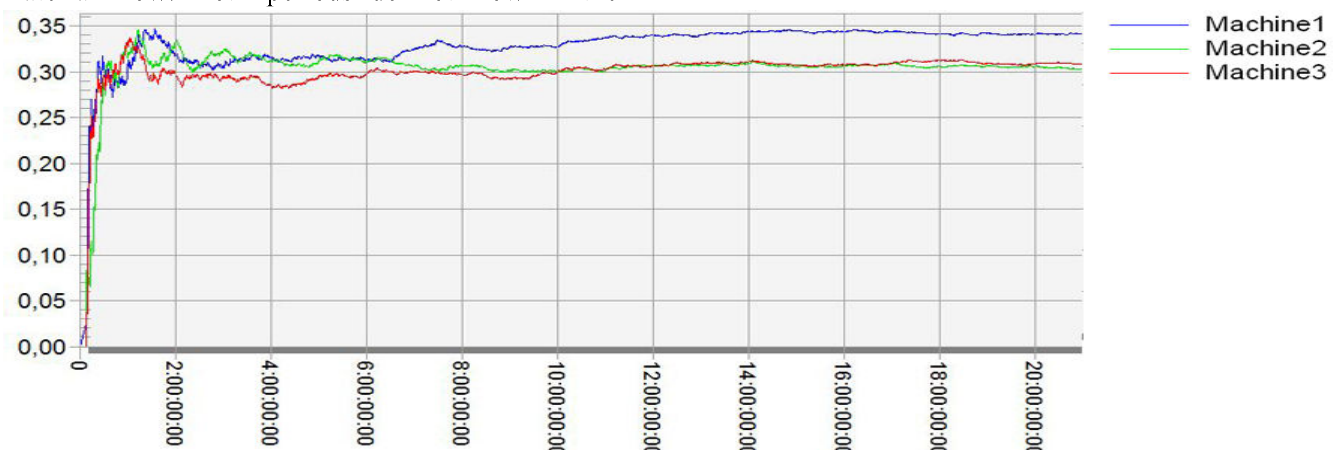

Figure – 7 Capacity utilization of workshop 2

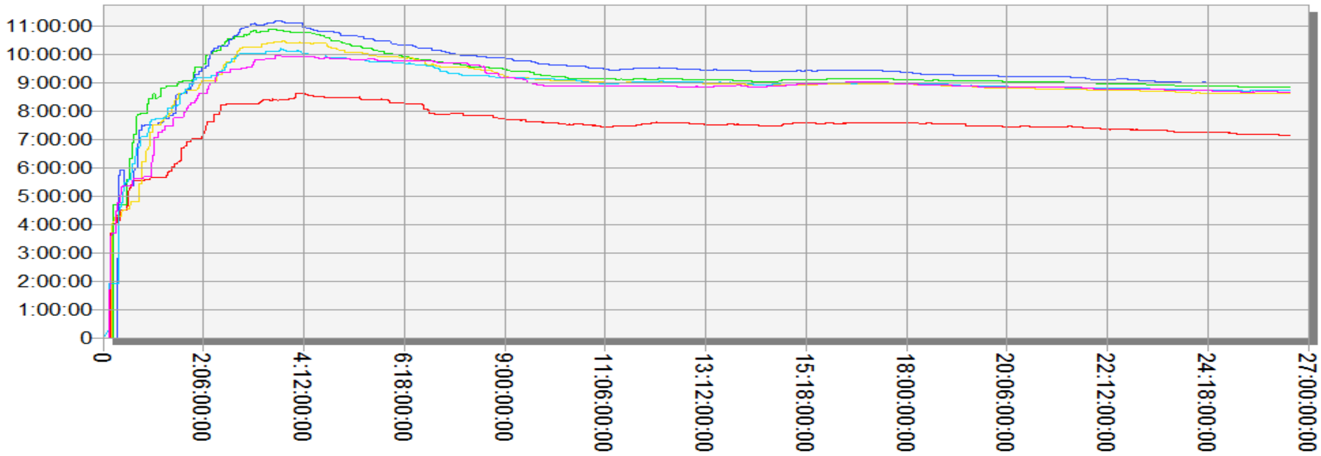

Figure – 8 Lead times of all six work piece types

determines the number of available processing alternatives for a work piece. Workshop 3 contains, in contrast to the other workshops, only two machines and therefore achieves the highest capacity utilization.

The lead times of the six work piece types underline this development. Figure-8 sketches the course of all types during the simulation. The covered period amounts the whole simulation run. The first two and a half day can be seen as the initial phase of the whole shop floor. The phasing-out period is left out.

At this point, the curves are even after the transient phase and end with a value of approximately nine hours. Work piece type one (red curve) defines the only exception with a generally lower lead time of seven hours. This results from the varying processing order of this type, which leads to a high flexibility for the redistribution decisions.

Overall, when applying an inventory limit of 60 minutes for the whole shop floor, the simulation results render an acceptable approximation of the desired limit value. The corresponding capacity utilization is qualitatively satisfactory. The courses of the machines show an even course with small deviations after the transient phase. In contrast, the quantitative results are not satisfactory, as the maximum utilization is only around 27.66% percent for the example workshop and 41% for the whole shop floor.

A repetition of the experiments with an inventory limit of 80 minutes leads to quite similar results with regard to the inventory limits (Figure-9 shows the results, using machine 2 as an example again). The average inventory of machine 1 amounts approximately 84 minutes. Machines 2 and 3 hold an average inventory of 87 and 94 minutes. The deviation is on average slightly better than in the first run and reaches from 1.8 up to 14.3 minutes. The uneven course of the inventories remains unchanged.

The capacity utilization for the example workshop during the second run improves from 27.66% to 43.91% (Figure-10). This improvement is remarkable, as the number of machines and the used order data stays unchanged. The course of the utilization is even, similarly to the first results with a smaller inventory limit of 60 minutes.

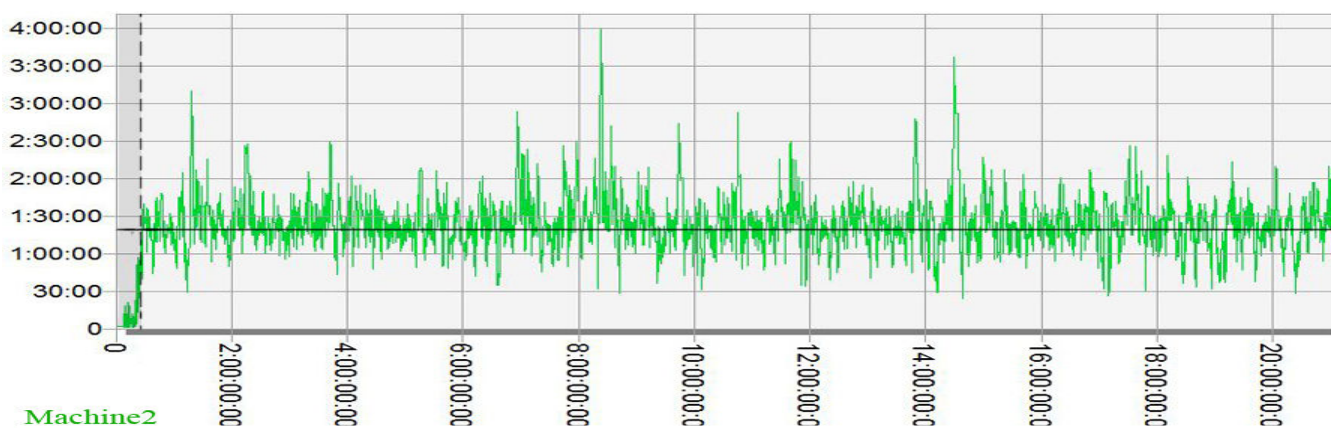

Figure – 9 Inventory course of workshop 2 with an inventory limit of 80 minutes

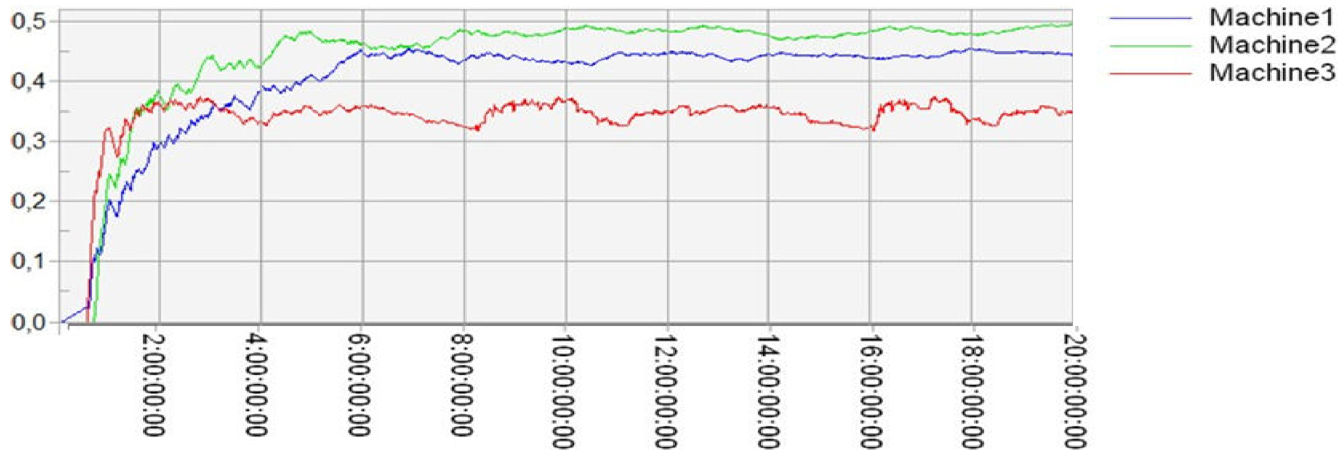

Figure – 10 Capacity utilization of workshop 2 for an inventory limit of 80 minutes

The increase of the limits reduces the lead times for all six work piece types (Figure-11). The maximum value during the simulation period is around 7 hours. Similar to the first run, work piece one shows the lowest lead time due to its variable processing order. For this work piece type, the value is around five hours. Overall, the reduction ranges between two and four hours.

6. CONCLUSION AND OUTLOOK

This paper presents an approach for the combined control of inventory and capacity utilization within a shop floor production. The control concept includes the use of artificial neural networks as inventory and capacity controllers in a cascaded control structure.

At this, the neural network for inventory control is responsible for the redistribution of work pieces between different workshops on the shop floor. Meanwhile, the neural capacity controller assigns single work pieces to available machines belonging to the respective workshop.

The evaluation of this approach by means of a generic material flow model shows a good performance relating to the compliance of the set inventory limit. The capacity results are changeable; they have a close coherence to the set inventory limits. A limit of 60 minutes for the whole shop floor leads to a low capacity utilization, while an increase to 80 minutes clearly improves the obtained results.

The close relationship between the inventory limit and the achieved utilization of the shop floor makes a dynamic and continuous adjustment of the set limit interesting for future research. Further, the composition of the order data and its effect on capacity utilization and inventory development should be investigated.

In the field of neural network research, the further development of the neural controllers is from major interest. At this, the possible suitability of different network architectures and configurations should be a central point. As the quality and performance of neural networks in practical applications is closely related to the learning process, the continuous learning of neural networks is very important. Therefore, the development of new, possibly hybrid network architectures should be advanced.

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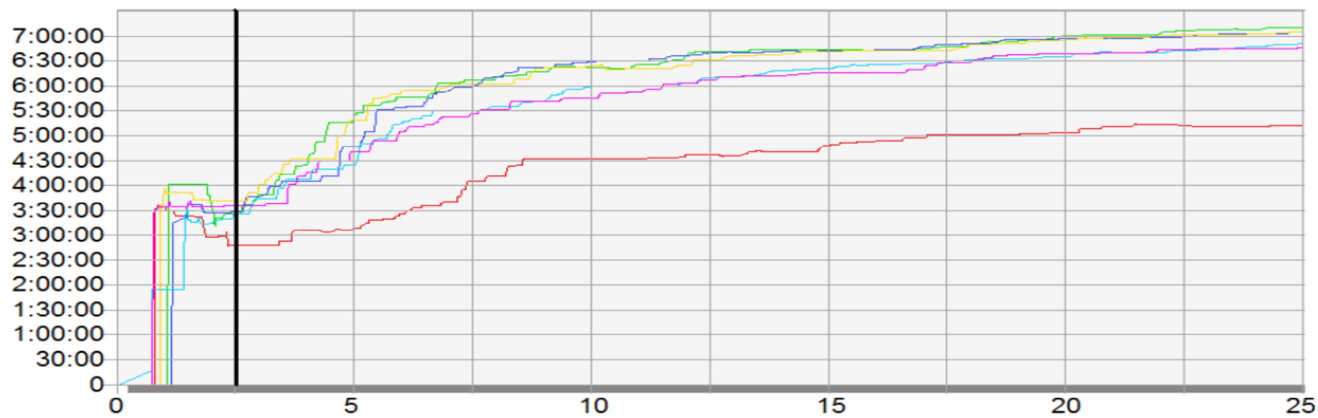

Figure – 11 Lead times of all six work piece types for an inventory limit of 80 minutes

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