Use of Artificial Neural Networks in the Production Control of Small Batch Production

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Abstract - *Our aim with this paper is to test a new performance measurement and control system for small batch production in the automotive industry with the help of Artificial Neural Networks. After the introduction of small batch production at an automotive company a possible use of this method for production control is presented.*

Keywords: Artificial Neural Networks; Logistics; Production control

1 Introduction

The foundation of a sustainable operations in manufacturing are stable and predictable production systems. Without adequate understanding of the factors – both internal and external – that affect those systems no business unit can operate in the long run. Studying and examining these factors alone is not enough though. During the research activities of the Department of Logistics and Forwarding the use of Artificial Intelligence emerged in the recent decade. Artificial Neural Networks in particular helped predicting and controlling logistics issues, such as:

- Warehouse management and performance monitoring
- Human resource effectiveness
- Prediction of defect product production

Our aim with this paper is to show the possibility of a new production control and performance management system based on the use of Artificial Neural Networks. First, we describe some earlier research of the Department than a possible solution will be presented for small batch production control.

2 Use of Artificial Neural Networks

During the last five years our Department used Artificial Neural Networks (ANN) for a series of logistics issues. Some of them will be detailed later. The reason for choosing ANN was the complexity of connections between logistics factors.

2.1 Artificial Neural Networks

Artificial Neural Networks are based on the arrangement and functional features of biological neural networks [4][7]. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. This learning phase is important for the use of the model. With enough data from the past the ANN is able to learn the connection between the input and output data. Parallel with the learning phase a test phase is taking place where the network is testing itself with other data from the same problem.

As a result, after the learning the ANN can be used to predict output data from input data. This is the most important result of this method. With this, we are able to use the trained algorithm for modeling the problem and use it as a decision making tool.

Various different types of artificial neural networks are proposed in the literature [4][7]. In our application we use Multi-layer Perceptron (MLP), which is one of the most widely known types of ANNs. The topological structure of the MLP type neural network is illustrated in Figure 1.

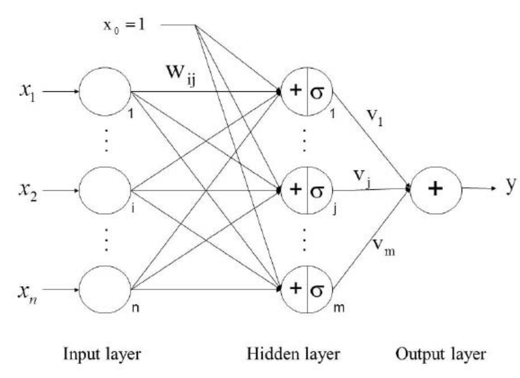

Figure 1: Topological structure of artificial neural network (MLP)

The network contains three layers. The input layer contains the inputs x_i. In the hidden layer m hidden neurons are applied. Between the input and hidden layers there are connection weights w_{ij} connecting the i-th input and j-th hidden neuron.

There is also a bias input $x_0 = 1$ with weight w_{0j} to the j-th hidden neuron. There is an output layer with output y. Between the hidden and output layers there are weights v_j connecting the j-th hidden neuron with the output.

The output of the neural network can be computed as:

$$y = \sum_{j=1}^{m} v_j \cdot \sigma\left(\sum_{i=0}^{n} x_i \cdot w_{ij}\right) \quad (1)$$

In (1) s is the sigmoid function:

$$\sigma(s) = \frac{1}{1 + e^{-K \cdot s}} \quad (2)$$

where K is the slope parameter of the sigmoid function.

2.2 Training Algorithm

Training or learning is the method of modifying the parameters (e.g. the weights) of the neural network in order to reach a desired goal. We can somehow classify learning with respect to the learning mechanism, with respect to when this modification takes place, and according to the manner how the adjustment takes place. In this paper the artificial neural network is trained in supervised, off-line manner by bacterial memetic algorithm [2].

Nature inspired evolutionary optimization algorithms are often suitable for global optimization of even non-linear, high-dimensional, multi-modal, and discontinuous problems. Bacterial Evolutionary Algorithm (BEA) [6] is one of these techniques. BEA uses two operators; the bacterial mutation and the gene transfer operation. These operators are based on the microbial evolution phenomenon. The bacterial mutation operation optimizes the chromosome of one bacterium; the gene transfer operation allows the transfer of information between the bacteria in the population.

Evolutionary algorithms are global searchers, however in most cases they give only a quasi-optimal solution to the problem, because their convergence speed is low. Local search approaches can give a more accurate solution; however, they are searching for the solution only in the neighborhood of the search space. Local search approaches might be useful in improving the performance of the basic evolutionary algorithm, which may find the global optimum with sufficient precision in this combined way. Combinations of evolutionary and local-search methods are usually referred to as memetic algorithms [5].

A new kind of memetic algorithm based on the bacterial approach is the bacterial memetic algorithm (BMA) proposed in [2]. The algorithm consists of four steps. First, a random initial population with N_{ind} individuals has to be created. Then, bacterial mutation, a local search and gene transfer are applied, until a stopping criterion (number of generations, N_{gen}) is fulfilled. BMA can be applied for training neural networks [1][3]. In this case the parameters to be optimized, which are encoded in the bacterium, are the w_{ij} and v_j weights of the neural network (see Fig. 1). The details of BMA can be found in [1][2][3].

3 Production process

The small volume production business unit of the automotive OEM has a diverse product mix and many machine set-ups for different production orders that take only 4-12 hours on average to complete. Quality issues arise caused by the many machine set-ups and various products, which results in unstable processes and high variability, as well as complexity. The business unit is an extended workbench and tier-1 supplier, which is focusing on increasing efficiency and productivity within a functional job-shop manufacturing layout with time-phased MRP planning and a multi-level dependent demand system.

The production system consists of three departments that contain all production processes from metal disc to final assembly of all the main products like doors, side panels, roofs, bonnets and hatches for premium small volume sports cars. The first department is the component production where metal components are pressed and laser cut out of aluminum or stainless steel discs that enter the facility pre-cut by a supplier.

The second department contains all the assembly processes where the final assemblies are put together out of two to four main components and several smaller purchased parts like reinforcement parts to increase the stability of the products. The third and final department is called “finish” and it is responsible to ensure proper quality in terms of surface quality (which can be impacted by difficult pressing processes) and dimension (which is mostly influenced by the different mating technologies used at the assembly department). At the end the final products are ready to be shipped to the main body shop and subsequently the paint shop of several internal customers of the production system. Furthermore, there is one more department within the small volume job-shop segment which is the project and process management department, responsible for launching new customer projects on time and to ensure continuous smooth operations of all running projects throughout their life cycle.

In addition to the small-series job shop the business unit contains four other, more or less separated segments which are: quality department, logistics, fixture construction and robotics (development and construction of the fixtures, manufacturing cells and robot programs for the assembly department and other customers), tool making (development and construction of pressing tools for the component production and other customers). The high degree of vertical integration makes it difficult to create an adequate value stream and material flow because processes with very different batch sizes and processing times must be tied together efficiently. Compared to normal production series the production system would be divided into two separate segments, one being the pressing plant and the other would be the body shop where relatively high amounts of Work In Progress (WIP) inventory are quite common. Therefore, it is necessary to have large amounts of inventory to balance the differences in processing time and batch size. Also asset utilization for integration of new projects into existing production assets is quite common, so not all the available time can be used continuously for series production, but also periodical time frames must be planned as implementation time.

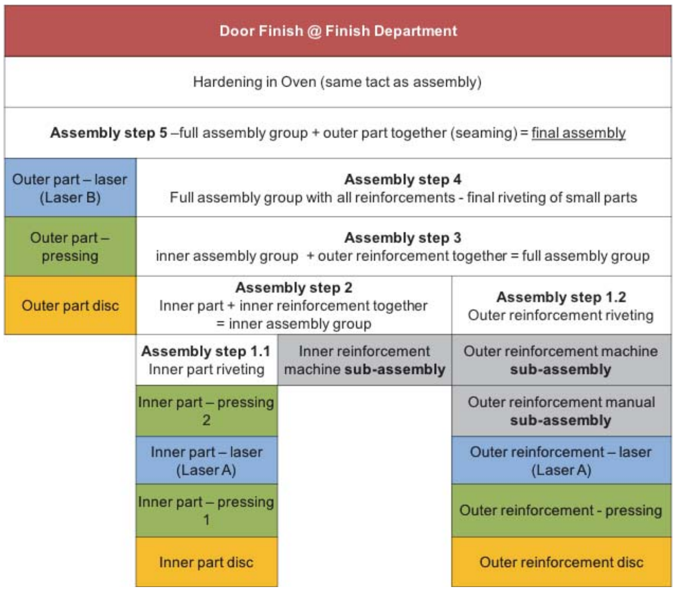

Figure 2: Example of the assembly steps based on the Bill of Materials

3.1 Need for production control

The above described production system – mainly because of the small batches – requires an adequate control and performance measurement system for the operation. The business unit is facing quality issues and continuous pressure from the customers for shorter lead time. With a tailor made control system the planning of the production would be able to serve the needs of the clients and enable long run effectiveness and sustainability of the business unit. In the next chapter a possible solution is described.

4 Proposed method

Our aim was to use ANN first for the prediction of the production planning accuracy. This accuracy is one of the most important factors in small batch manufacturing. If this accuracy is high enough the production can fulfill the orders in the given time window and can achieve competitive advantage in the long run.

As an input the following data will be used:

- Production quantity
- Production complexity (number of assembly steps)
- Capacity utilization

As an output we regarded the production planning accuracy. This setup can be seen in the following figure

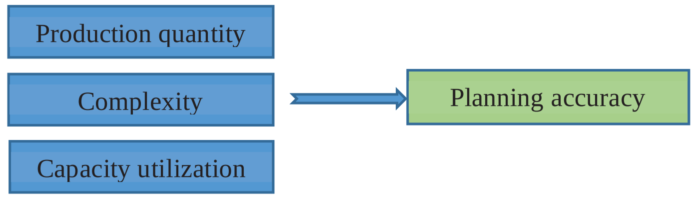

Figure 3: Input and output data of the model

With enough data of previous production shifts – together with the measured accuracy of production planning – we will be able to simulate this output value with changing the input data according to the production plan. This could be used as a decision making tool: By given number of orders (fix production quantity and complexity) the adjusting of capacity utilization – by adjusting maintenance time for example – can increase the accuracy of production planning. Or, the other way around, by given maintenance time or pre-defined capacity utilization the number of orders will give the predicted accuracy thus helping the production control with possible output of the current shift - even before production started.

Table 1: Example of collected data

Production quantity	Complexity	Capacity Utilization	Planning accuracy
200	4	0.90	0.95

We collected data for the testing of our method. With this data at hand we started the simulation with the following parameters:

4.1 Test of the method

With these collected data we performed 10 simulations using 6 hidden neurons and the mean relative error (MRE) of the train and test set was investigated which is defined as:

$$MRE = \frac{1}{p}\sum_{i=1}^{p}\left|\frac{y_i - t_i}{y_i}\right| \quad (3)$$

where y_i is the output of the network for the i-th pattern, t_i is the desired output for the i-th pattern, and p is the number of patterns. With the trained algorithm we performed further evaluation of the test results.

We created three scenarios for the testing of the algorithm. The best scenario was a large quantity order with few assembly steps (complexity) and average capacity utilization. According to our assumption these parameters will give the best output (production accuracy). The worst scenario is a low quantity order with complex assembly and high capacity utilization.

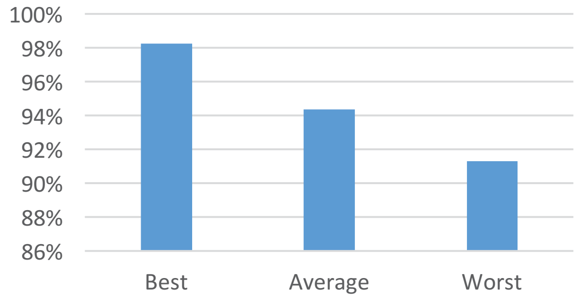

Figure 4: Planning accuracy based on the scenarios

5 Conclusion

This test showed the viability of our model. The accuracy of production planning given as a result of the trained algorithm follows our assumption: Bad scenario result in lower level of accuracy. Further data collection can enhance the weights and thus the algorithm. Long term aim of our research is to give the production control this tool for daily use in planning operations.

6 Acknowledgements

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