Use of neural networks to improve energy efficiency in production

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Abstract

Due to its high share in CO2 output, the manufacturing sector is in the focus of public interest. In consequence of limited energy resources as well as growing environmental and climate awareness, decreasing the use of fossil sources gains importance. In addition, the average electricity prices for industrial customers rose by more than 85 percent in recent years. An optimization of the energy efficiency is thus a way to stay competitive in the face of the increased energy costs. The objective of the article on hand is the development of a new approach to optimize energy efficiency through the use of neural networks in machine scheduling. The goal of the neural network is the identification and selection of an energy-optimal priority rule for a variable job structure. Therefore, in the first instance, a simulation environment is developed based on theoretical principles. The effects of different methods of machine scheduling on energy efficiency are evaluated by simulating various scenarios. The analysis of 624 test setting runs in the simulation environment shows the applicability of neuronal networks in machine scheduling and the ability of these systems to improve energy efficiency in a manufacturing environment. In summary, it can be stated that different priority rules should be applied in terms of energy efficiency for different job structures. Furthermore, it was found that the First-Come-First-Serve-Rule leads to the best results in more than half of the studied machine scheduling plans.

Keywords: energy efficiency, neural networks, machine scheduling, simulation

Introduction

In the manufacturing sector, in addition to an increasing importance of environmental image in the population it is the economical factor that is of great relevance. Over the past years the average electricity prices for industrial customers rose by more than 85 percent (BDEW 2013). In face of the increased cost pressure, the optimization of the energy efficiency is one way to stay competitive. Apart from the continuous price increase for electricity, there are further drivers that lead to a raising awareness of energy efficiency in production. These include a growing energy demand, reduction in energy reserves, proven ecological damage from energy generation and use as well as increasing restrictions by the policy (Müller et al. 2009). The starting points for increasing energy efficiency in the manufacturing sector are manifold. In this article the possibility of an energy-efficient job processing in production is supposed to be considered. In general a distinction between optimized job controlling and system control is made (Müller et al. 2009). In an optimized job control the load profile of the machines, which are involved in the production, is modified with regard to the energy criteria, for example, by time-delayed ramp-up of the machines. The energy consumption can also be reduced by optimizing the control system (Müller et al. 2009). In this article the approach of the optimized job controlling is tracked. The machine scheduling will be used as a tool. In the literature the concept of machine scheduling is used synonymously with the terms sequencing, sequence planning and detailed planning (Günther et al. 2007). The assignment of jobs to be processed on the available machines describes the meaning of the term machine scheduling. In general, machine scheduling takes place immediately prior to production realisation (Neumann 1996).The applicability of instruments of the relatively new discipline of neuroinformatics will be considered as part of an energy-efficient machine scheduling. The aim of this article is to identify and evaluate a possibility to reduce the energy consumption in production by using neural networks from the field of neuroinformatics by an optimized machine scheduling.

Objective of energy-oriented machine scheduling

In the context of machine scheduling the overriding goal of cost minimization is pursued within traditional production planning and control systems (Corsten et al. 2012). However, the recognition and measurement of monetary terms in machine scheduling is complicated. Consequently, monetary goals in theory and in practice are usually substituted by time-related goals (Jung 2010). These goals can be distinguished between job-related and machine-based time goals as shown in Table 1 (Corsten et al. 2012).
In this particular case, measures to increase energy efficiency by means of machine scheduling are more important than the time goals. Factors which can be regarded are costs

for starting up machines at the beginning of the day or the idle time of a machine when it is not busy for example. Therefore, the aim is the reduction of electricity purchase costs incurred in connection with the use of machines. The basis for this observation are the fictitious load profiles of machines (see Figure 1), which can be divided in the five sections: ramp-up (Phase I), production (Phase II), idle (Phase III), shutdown (Phase IV) and standstill (Phase V). The energy consumption of the machine is thus calculated by integrating the curve shown in Figure 1. During the ramp-up, the shutdown and production, the structure of the load profile cannot be changed by the machine scheduling, consequently the idle times are of interest here. As a premise of the following analyses, a positive correlation between minimizing the idle time and increased energy efficiency is required.

Neural networks for solving the energy-oriented machine scheduling

In the literature the solution of machine scheduling problems is distinguished between optimisation procedures, heuristic methods and methods of artificial intelligence (Evers 2002). The methods differ in their solution quality and computation complexity of each other. In practice, the heuristic method are mainly used (Günther et al 2007). The reason for this is the relatively high solution quality compared to the limited quality of computation.
This article outlines a methodology to solve the machine scheduling problem with the help of neural networks as a method of artificial intelligence. The advantage of neural networks is located in the non-linear characteristics, which make it possible to model a large number of ratios. Furthermore neural networks are suitable by its adaptation capabilities and high robustness regarding to low-quality data for the process of complex problems (Scherer 1997). Other positive attributes are its fault tolerance and ability of sel-learning (Kratzer 1993). In consequence neural networks have a wide range of application. For instance, it is used for pattern recognition, optimization, classification or forecasting purposes (Scherer 1997). Basically, neural networks are understood as information processing systems, which consisting of several interconnected processing units, known as neurons. (Zell 2000). In general, a neuron has multiple inputs and a single output (Braun 1997). Input values of the considered neuron represent the output values of a previous neuron. The exchange of information between neurons takes place via weighted connections (Lämmel et al. 2012). The weighting value of a connection illustrates the intensity of the influence of a neuron to another (Lackes et al. 2000). In principle the neurons of a neural network are arranged in multiple layers (see figure 2). In the literature a distinction between input and output layer and one or more hidden layers is made (Stoica-Klüver et al. 2009). Thus, there exist input, output and hidden neurons: input neurons receive the input values from the environment and output neurons transfer the output values to the environment. In contrast, hidden neurons have not any contact with the environment, but to other neurons. The self-learning or adaptation of neural networks is made to the current situation by developing new

connections, removal of existing connections (Schmidt et al. 2010) or by changing the connection weights (Bothe 1998). In this particular article input values are fictitious job data. These data differ in the job volume, the job arrival rate, the number of operations per job and the processing time of an operation. The output values represent rules regarding the job of processing of jobs of machines, so-called priority rules. Depending on the variation of the job data it can be assumed that different priority rules imply different quality respect to the energy efficiency.
Therefore the neural network determined the priority rule to be used for each case on the basis of fictitious job data. Based on this priority rule an energetically optimal machine usage plan is developed from the job data.

Model construction and evaluation of the results

As a basis for investigating the use of neural networks to improve energy efficiency in the production, a dynamic stochastic job shop problem is considered. This problem is a machine scheduling problem in terms of job shop production with continuous incoming jobs and parameters that follow a probability distribution. In this job shop production, there are three machines and it can be used the following priority rules (Nebl 2011):

- Shortest Job First-Rule (SJF): The highest priority gets the job with the shortest operation time.
- First Come First Served-Rule (FCFS): The job, which came in first in the sorter, is given the highest priority.
- Last Come First Served-Rule (LCFS): The job, which is entered as the last in the sorter, is given the highest priority.
- Shortest Gross Immanent Operation Time-Rule (SIO): The job with the shortest total processing time is given the highest priority.

The inputs and outputs variables of the neural network are mapped accordingly in Figure 3. Using the simulation results of energy-oriented machine scheduling the postulated thesis, that depending on the variation of the job data, different priority rules have the highest quality based on the energy efficiency, is occupied. Thereby, all scenarios are clearly dominated by one rule. 56 percent of the generated scenarios show the best results in terms of energy efficiency using the FCFS-Rule. The SJF-Rule provides in 20 percent of all cases the most energy efficient solution. LCFS- and SIO-Rules constitute 14 and 10 percent. The energy savings from the usage of different priority rules are, however, very low. The maximum percentage change in the energy efficiency is only 1.29 percent.

Conclusion and outlook

In this article the increase in energy efficiency in production through an energy-oriented machine scheduling using neural networks is investigated. Above all, the influence of different priority rules on energy efficiency is focussed. It is shown that the FCFS-Rule has the best results with respect to energy efficiency for more than half of the investigated machine usage plans. In summary it can be said that for different scenarios different priority rules with regard to the energy efficiency are to be applied.
In future research a validation of results with real-life data is required. By using real data, the quality of the developed neural network could be tested in real world scenarios. Furthermore, the complexity of the problem considered here is limited, as a job shop production is observed with only three machines. An extension to include additional machines would increase the proximity to industrial practice. Furthermore, the precision of the neural network can be additionally optimized. As well, it can be assumed that by this procedure, the robustness of the model can be increased.

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Appendix

Table 1: Overview of possible objectives of machine scheduling

Job-related time goals	Machine-based time goals
Minimizing processing times	Maximize the capacity utilization
Minimizing the schedule variances	Minimizing the setup times
Minimization of transport times	Minimization of idle times
Minimizing waiting times	Minimization of the total occupation times

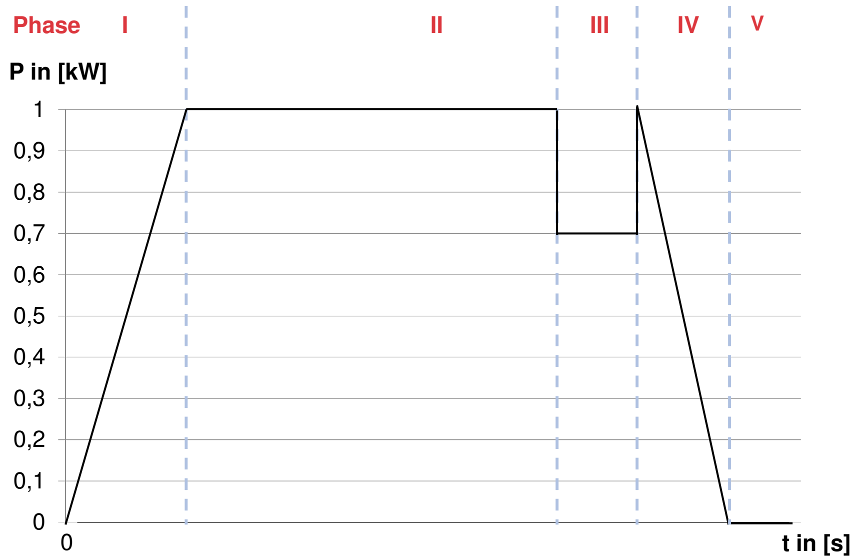

Figure 1: Structure of a load profile

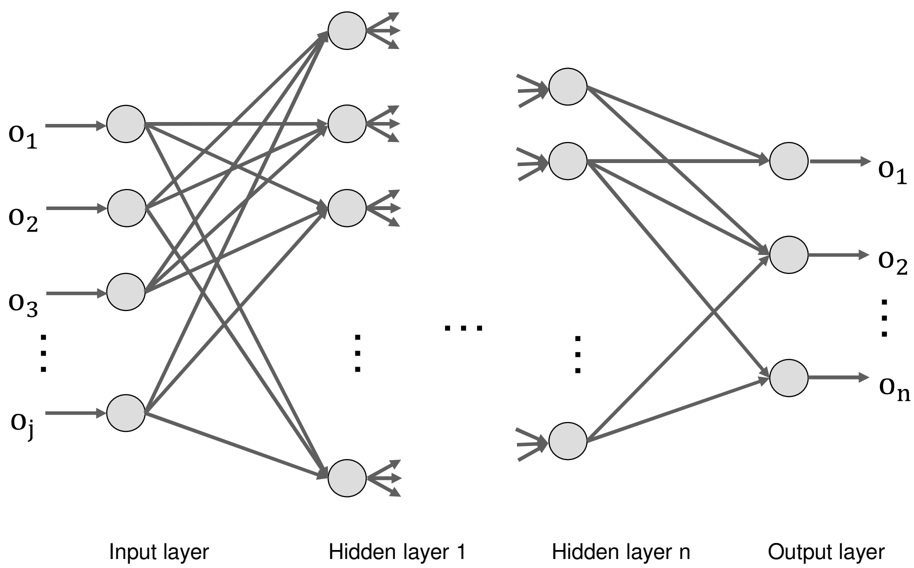

Figure 2: Depiction of a multilayer neural network (based on Lippe 2006)

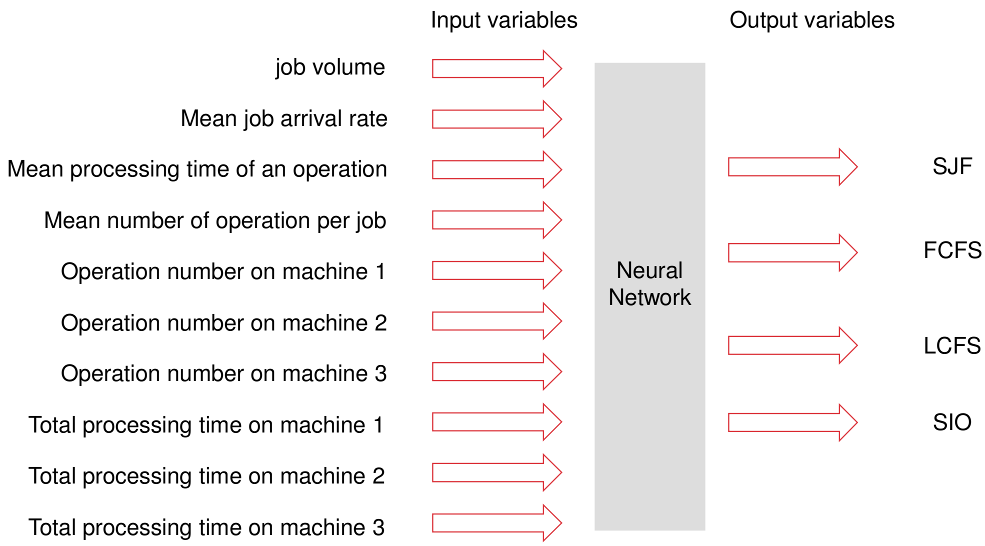

Figure 3: Representation of the used input and output variables