NEURAL NETWORKS FOR PROCESS CONTROL IN STEEL MANUFACTURING

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ABSTRACT

Neural Networks are particularly suitable for the approximation of non-linear time-variant functions. Due to their learning capabilities, they have proven useful in control applications for complex industrial processes. In collaboration with the Corporate Research and Development Department, the Siemens Industrial and Building Systems Group developed Neural Network applications for the steel industry, resulting in a more economic use of resources and an improvement of productivity. At this time Siemens has installed more than 100 neural nets world wide at various plants.

1. INTRODUCTION

Since neural networks can learn and adapt on-line, they make it possible to model and control physical phenomena that are not fully understood. The underlying physical process does not need to be completely analysed and analytically modeled.

Current automation and control systems in the steel industry are based on physical process models, combined with simple on-line adaptive techniques. Although engineers attempt to optimize the model parameter configuration for the plant in the commissioning phase, this is not always possible as situations can arise in which knowledge about the system is only available in the form of sets of measured data. In such cases neural networks are beneficial, because they can reveal structures and dependencies that are concealed within the data. Neural networks are therefore becoming an integral component of the steel manufacture automation system. At present, most applications of neural networks in the steel industry are at automation level 2 [1]. Here they provide the basic level automation (mostly classical PID-controllers) with set points. This means that the nets are mainly applied in the feed-forward path of the control system, and not within the feed-back loop. Therefore a stability proof, which is usually very difficult for systems with nonlinear components (such as neural networks), is not required.

2. APPLICATIONS IN THE STEEL INDUSTRY

For many years, neural networks from Siemens AG have been applied to the process control of flat steel rolling mills (fig. 1) and electric arc furnaces. Typical applications are,

Figure 1. Rolling mills with neural control.

for example, prediction of the temperature of the stock in the rolling gap, of the width variations in the roughing mill and the finishing mill, of the temper of the stock, or determination of the optimal actuator curve of the edger rolls in the roughing stand (short-stroke control), so as to form as close as possible to rectangular ends of the strip (strip head and strip tail) [2] [3] [4] [5]. Three applications will be explained in detail in the following sections.

2.1. Electric Arc Furnaces

Steel scrap is melted in electric arc furnaces to produce high grade steel [6]. Even though the energy in the primary fuel is not used for direct heating, but instead converted into electrical energy, the overall efficiency of such plants is so high that they account for 30% of all raw steel produced worldwide. The arc furnace production method is gaining in significance because it is energy efficient and because scrap is plentiful and it has a high intrinsic energy content. The principle factor determining the profitability of these furnaces is the extent to which they achieve the highest possible level of power conversion. Because of the unavoidable changes in furnace parameters that occur during the melting process, there was, until recently, no generally accepted control system capable of providing optimal energy utilization throughout the operational period.

Recently, however, Siemens has developed a method of optimizing electric arc furnace control so that the highest possible power is continuously fed into the process. This involved developing a new analytical model (fig. 2) that was combined with a neural network to form a hybrid model. As the neural network - and thus the hybrid model - can

Figure 2. This hybrid model optimizes the operation of an electric arc furnace under constantly changing conditions.

Figure 3. Neural network-derived optimization increases active power of the smelting process while satisfying all boundary conditions

Figure 4. Predicted lateral flow error in one of Thyssen's rolling mills

be adapted and optimized on-line, the ideal operational parameters can be determined. The method was implemented and tested at a pilot plant run by Krupp Nirosta, in Bochum, Germany in January 1994. Since September 1994, the method, which is based on the most accurate adaptive model of a furnace to be found anywhere, has been managing Krupp-Nirostas main furnace producing stainless steel. The furnace has a run-off weight of 150 t and a capacity of 720,000 t/a. Krupp's Bochum pilot plant has demonstrated that the efficiency of the main furnace could be increased substantially (fig. 3), which would reduce energy costs by the order of one million dollars a year. Tests also indicate that an overall increase in productivity could be obtained, which would in turn result in an enormous reduction in production costs.

Technical background

From an electrical engineer's point of view, the arc furnace is an unbalanced load with non-linear, time-dependent characteristics. It is operated using a star configuration with a floating star point. The optimization model based on the hybrid model provides the optimal setting parameters, which are in turn maintained at a constant level by a cascaded regulating circuit. This means that the furnace operator can choose the method best suited to operating the plant according to the boundary conditions he himself specifies. The boundary conditions are in turn obtained from cascaded optimization calculations which, among other things, make trade-offs between the maximum power absorption (resulting in the shortest melting time) and increased thermal stress. The weighting of these incompatible target variables can be tailored by setting economic and legal parameters. In all, this method provides an intelligent tool that makes it possible to maintain required target variables. There is no reason why the principles behind it should not be applied to similar problems relating to process automation, particularly in power plant optimization.

2.2. Wide-Strip Hot-Rolling mills

Recycling bears a remarkable potential to save energy and raw materials. For example, scrap from steel forming is led directly back to the production process. However using a neural network based, improved automation system, the amount of scrap is reduced and unnecessary recycling is avoided. This is demonstrated by the automation of wide-strip hot-rolling mills [7].

2.2.1. Prediction of the natural spread

Assume that a customer wants sheet steel of precisely 1.8m width. Normally, this would be accomplished by rolling the sheet steel so that it had, on average, an excess width of several mm to take variations in the production process into account. The scrap would then be trimmed of, melted down again (e.g. in the electric arc furnace) and reprocessed. But by using neural networks it is now possible to reduce the excess width by an average of 1mm. Reducing recycling by these means has led to saving in the region of several millions DM a year (fig. 4), (fig. 5).

Why then roll the sheet so that it is slightly too wide in the first place? The reason is that the material is pre-rolled in the roughing mill before it is brought to its final thickness by a finishing mill with seven horizontal rollers. The width of the sheet can only be controlled at the pre-rolling stage by the vertical rollers. In the finishing mill the width of the band is altered, depending on the materials being milled and the state of the finishing mill itself. To prevent the sheet being too narrow after finishing, a safety margin, the

Figure 5. A neural network can improve the accuracy of the predicted lateral flow in a steel rolling mill by 1 mm.

Figure 6. a hybrid system of neural net and conventional model.

excess width, must be built in. There is no adequate physical or analytical model for lateral flow. Neural networks, however, can be advantageous in this situation. They can learn which width must be set at the vertical rolling stage to obtain the width specified by the customer at the end of the finishing stage (fig. 5). This relationship is not just a function of the width of the finished product. The characteristics of the materials used (e.g. composition) also play a significant role. Dynamo steel, for instance, has different characteristics from the steel used in making coins. The parameters of the finishing mill are another factor that has to be taken into account. The reduction in thickness produced by the rollers and the temperature have to be determined for each sheet.The neural network has to learn about all these effects from examples; however, such examples are easy to obtain from previous rolling operations.

2.2.2. Prediction of Rolling Forces

Neural networks can also be used to predict rolling forces. The rolling force for each of the rollers in the finishing mill is set by means of conventional feedback controllers so that a specified thickness is obtained. The operating points of the controllers must be preset to prevent transients at the start of rolling from reducing quality. This prevents the waste of raw materials and thus saves energy by eliminating settling waves at the start of the strip. The neural network learns a mapping in the same way as it handled the lateral flow problem. In this case, the mapping depends on more than 20 inputs. There are physical-analytical models that predict rolling forces, but they require a lot of time and effort to set up and are, in any case, not sufficiently accurate. This is why a hybrid approach has been adopted. The Neural networks learn in what regions the accuracy of the analytical model is inadequate and correct the rolling force predicted by the model accordingly. The result is an average increase in accuracy of more than 20 %.

2.2.3. New Methods

Complex applications in process automation would not be possible without the use of new methods. First attempts with standard methods, such as static mappings with MLP or RBF-Networks, failed. It was only with the use of hybrid systems and on-line adaption that the desired level of success was achieved.

Know how is also required concerning pre- and post-processing of the neural network input and output data. The proper choice and application of methods for e.g. data scaling and elimination of invariances is crucial.

Use of "A Priory" Knowledge, hybrid Systems

For many of the above mentioned applications there is some a priory knowledge about the underlying physical processes. There are different approaches to exploit this knowledge: "if-then-statements" about the process are incorporated using methods of "Neuro-Fuzzy". If a controller with an analytical model exists, the model is combined with a neural network in a hybrid system (fig. 6). The neural network learns to correct the model output in regions where the model performs poorly. Another advantage of the hybrid system is a possible detection of extreme errors of either the analytical model or the neural network by an exceptionally high correction value.

On-line Adaption

For high accuracy of the neural controller, the day-to-day performance of the rolling mill must be taken into account. Undetermined or concealed parameters such as wear and tear can have a considerable influence on the control.

On-line adaption accounts for day-to-day performance. After completion of each production cycle a so-called "post-calculation" is carried out. Using measured values the real plant state and control quantities are determined. According to errors between the post-calculated and the desired or pre-calculated values some neural network weights are

Figure 7. Without on-line adaptation after a few days the error in temperature prediction increases considerably.

adjusted in order to minimize the errors. The adaption cycle thus includes: pre-calculation, process execution, post-calculation and provision of the new adaptive parameters for the next production cycle. On-line adaption must be sufficiently robust to maintain stability under all conditions. New techniques and new neural network topologies are used to ensure stability even under tough operating conditions.

As an example, the effect of on-line adaption on temperature prediction is illustrated in fig. 7. The root mean square error (RMS, smoothed) is plotted against the running number of the slab. 9000 strips represent about one months production. The error with on-line adaption remains rather constant (lower curve), whereas without on-line adaption the error increases dramatically (upper curve).

Initial Learning

Usually neural networks have to be trained with a representative plant data set before they can generalize to new data and thus can securely take action within a controller. However, to build a representative data set for a steel mill typically takes several thousand strips (i.e. several week's production). Such waiting times are not acceptable when commissioning a new plant or a new controller. It is also not desirable to employ additional conventional modules, whose only job would be to guarantee sufficient operation in this training phase.

Consequently, "Initial Learning" methods have been developed that adapt to each single data point, starting from scratch, however resulting in reasonable on-line behavior at new data points.

For "Initial Learning" a hybrid system composed of an analytical model and several on-line adaptive neural networks is used. Starting with a very small network, increasingly large neural network structures are build up automatically while the size of the data base increases.

"Initial Learning" is employed, if

- new plants or plant components are commissioned that are controlled with neural components,
- conventional controller components are exchanged with neural networks at existing plants and no data collection is available.

At CSP-mills, using "Initial Learning", high quality control, comparable to control with off-line pre-trained networks, was achieved after only a few operation days.

3. CONCLUSIONS AND FUTURE PROSPECTS

For many years, neural networks have been successfully used for second level process automation in the steel industry. They have applications in the optimization of electric arc furnaces and in the prediction and control of rolling forces, material properties, width, width shape and temperature in steel mills. Neural control leads to an increase in production, to energy saving and to the avoidance of unnecessary recycling, which results in an enormous reduction in costs. An important prerequisite for the successful use of neural networks is their on-line adaptive ability directly on the plant. In this way they can adapt to meet the day-to-day performance of the mill. The commissioning of the nets is simplified and speeded up by using an "Initial Learning" phase. The concept behind the techniques described above can be applied to many areas in which nonlinear modeling, hybrid modeling, and the optimization of nonlinear target functions under any nonlinear boundary conditions are required.

The further development of these methods will bring us closer to the goal of "intelligent" steel production plants. The objective is to develop concepts based on neural networks that will be used at the two highest levels of automation (production control and management systems). The immense potential of this approach can then be used to create integrated production techniques that vastly improve the efficiency and competitiveness of entire industries while reducing demand for natural resources.

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