Neural-Network Control in the Metals Industry

Edward Wilson
SAI International
454 Barkentine Lane
Redwood Shores, CA 94065-1126
ed.wilson@alum.mit.edu

Abstract

Because of their capabilities for adaptation, nonlinear function approximation, and parallel hardware implementation, neural networks have proven to be well suited for some important control applications. This paper briefly presents three examples of neural-network control applications on laboratory and industrial hardware. An overall problem-solving approach is presented as well as suggestions for neural-network research that will benefit industrial control optimization.

1. Introduction

Several examples of the use of neural network (NN) technology in control applications are given in [2]. Often when applying NNs for control, the central question is when -- and how -- will the incorporation of neural network components provide a clear, cost-effective advantage in real-time control?

When answering this question, the NN's capabilities (generic nonlinear functional element, efficient adaptation, and possibility for parallel hardware implementation) must be considered against the costs (nonlinear optimization, black box, and lack of stability proof). In the NN applications presented here, it has been found that using the NN as part of well-designed system is important. Control system architecture and the targeted use of NN (in locations where the benefits outweigh the costs) has been found to be more important than NN-specific issues such as NN architecture or NN training enhancements.

1.1 NN Training is gradient-based parameter optimization

When the backpropagation (BP) algorithm [3][4] is used to train feedforward NNs, training can be viewed as a special case of gradient-based parameter optimization (GBPO), as presented in [1]. Application of NNs is equivalent to solving GBPO problems with the following special characteristics:

1. BP is efficient for finding derivatives - calculation of derivatives on backward sweep through dynamics is on the same order as the forward sweep.
2. The generic nonlinear aspect of the NN is valuable - knowing the exact form of the functional element required is not necessary, although it is helpful.
3. Parallel hardware implementation is possible.

Because of this, several issues present in parameter identification (e.g., ARMA modeling, etc.) are present here, including: selection of sample rate, sufficient data, minimal but sufficient degrees of freedom in model, data pre-filtering, selection of tapped-delay-line inputs, handling outliers, etc. This leads to a significant pre-processing effort. Due to the increased functional capabilities of NNs, it is especially important to try to match the model architecture to that of the underlying process. Excess degrees of freedom increase the need for and reliance upon process data.

1.2 NN Application methodology

This has led to a staged development approach, summarized as follows:

1. Select the control system architecture that best fits the control problem (e.g., indirect adaptive control, generalized predictive control, etc.)
2. Identify the location in the control system that warrants application of a NN solution (cost/benefit analysis).
3. Solve the problem using a fixed linear element in the location where the NN will be used. It may be possible to use existing control theory to calculate an optimal solution here.
4. Adapt the linear element based on the available data.
5. Implement an adaptive NN element in parallel with the adaptive linear element. Alternatively, the linear functionality can be implemented by the NN.

This approach has the advantage of being tied closely to the vast amount of existing control theory and methodology. It is also useful since after step (5) a fair evaluation can be done to determine the benefits of adaptation and the NN.

2. Application examples

2.1 Reconfigurable control of a free-flying space robot

A laboratory prototype of a free-flying space robot, developed at the Aerospace Robotics Laboratory at Stanford University, was used as a platform for development of technology related to several areas of NN Control [5][6][7]. One specific control problem that was addressed was the need to reconfigure the control system in response to multiple unknown failures of the nonlinear actuators (on/off gas thrusters). The solution involved an indirect adaptive control architecture that used a recursive least squares solution to identify failures based on (noisy) accelerometer data. Use of the NN was targeted at the nonlinear thruster mapper portion of the control system. Using conventional, linear control technology wherever possible, the system was able to reconfigure and stabilize itself within four seconds. The NN training then progressed autonomously to eventually implement the optimal solution.

2.2 History and focus of the company:

SAI International includes what was formerly the metals industry division at Neural Applications Corporation. SAI supplies intelligent software based process control technologies to the metals processing industry worldwide, with special emphasis in electric furnace steelmaking.

2.3 The Intelligent Arc Furnace Ò

About 40 Intelligent Arc Furnace (IAF) controllers have been installed worldwide since 1992. The IAF uses neural-network technology to regulate the electrical energy input in an Electric Arc Furnace, used in steelmaking. By adapting to changing system dynamics and material mix, the IAF reduces energy consumption, reduces electrode consumption, and increases throughput, saving up to $1M per year for the steelmaker.

The NN used in the IAF is trained using backpropagation, and the control system is similar to a generalized predictive control architecture. The process is very nonlinear, poorly understood, and constantly changing. These features suggest the use of a neural

network solution. In short, the data availability outweighs process understanding. Although there are 40 installations worldwide, each process is different, and the generic functional aspect of the NN has helped here, minimizing the need for manual redesign at each installation.

As an extension to the IAF, a prototype is under development at North Star Steel – Minnesota that will extend optimization to include all energy inputs, including gas, Oxygen, and Carbon [8].

2.4 Green-sand controller

"Green Sand" is the term used for sand used in casting molds. The right consistency of sand is important to producing a good casting, and this is the part of the process that has been optimized. Specifically, the "process measures" of compactibility, the available bond in the sand, and the water to clay ratio in the sand are computed. The control problem, then, is to determine the optimal amount of water addition (typically in gals/min) and bond addition (typically in lbs./minute) such that "measured process measures" are as close to the "desired process measures" as possible.

The major challenge is that the measurements are taken up to two hours after the relevant control variables are implemented. A BP-based NN model is used to predict the final outcome, and the output of this model is used as a "virtual sensor" in the control system.

Discussion:
We tend to find that in these neural-network control problems, the (1) appropriate architecting of the control system, (2) use or development of appropriate sensors, and (3) "cleaning" the data using standard statistical approaches and filtering, are all critical to the success of the application. The neural network is far from a magic bullet, but if the previously mentioned steps are done well, the NN will be able to achieve better performance than a linear adaptive controller, since it has greater functionality.

We use the NN as an adaptive nonlinear functional element that needs data to determine its functionality. We have experimented with many different architectures, but mostly use a slightly modified version of feedforward networks trained with Backpropagation.

3. Needs in Industrial NN Control

Based on the experience gained in developing the applications described in Section 2, the following needs have been identified:

- Tools to improve NN architecture selection and selection of NN inputs, including combining inputs during pre-processing
- Technology that deals with realities of industrial control such as:
  - Sensor/actuator degradation or failure
  - The form of dynamics may not be clear (# taps, transport delay, etc.)
  - Relatively limited data, as compared to noise level and response time requirement
  - Presence of noisy (non Gaussian, non white) data
- Faster optimization is generally *not* an issue
- It is desirable for the solution to be tied closely to classical approach. The "black box" issue is a problem.

4. Suggested Research

A problem with neural-network research is the often-empirical nature of research results. This is due to the nonlinear aspect of the technology, meaning that theoretical developments are difficult, and often limited in practical utility. Most results are empirical, meaning that a particular problem was addressed, results presented, and conclusions drawn (as with the research presented here). This issue suggests the following approach, which hopes to maximize the usefulness of research results:

- Solve a particular real problem with real data (including issues listed in Section 3) if possible.
- Solve the problem first using the best available methods, without using a NN.
- After solving the problem using NNs, the value of NN can be evaluated more objectively.

5. Summary

An approach to applying NN technology to control applications has been presented. The main features of this methodology are:

1. The NN is used as a tool within a standard control system architecture where its benefits outweigh the costs of development.
2. NN training is viewed as a special case of a gradient-based parameter optimization problem, so issues such as sample rate, data cleaning, etc. must be addressed.
3. A staged development, starting with a linear element and progressing to an adaptive neural element is used. This simplifies development and enables objective evaluation of the benefits of adaptation and the use of the NN.

Combined, these features lead to a more control-based solution vs. a pure NN approach.

Some specific needs for industrial control have been presented, mainly focusing on the "real world" aspects of these problems. Research areas have been suggested aimed at using the given methodology to address the real problems presented here.

References:

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References [5], [6], and [7] are available in .pdf and .ps formats at http://sun-valley.stanford.edu/bib/arlpub.html