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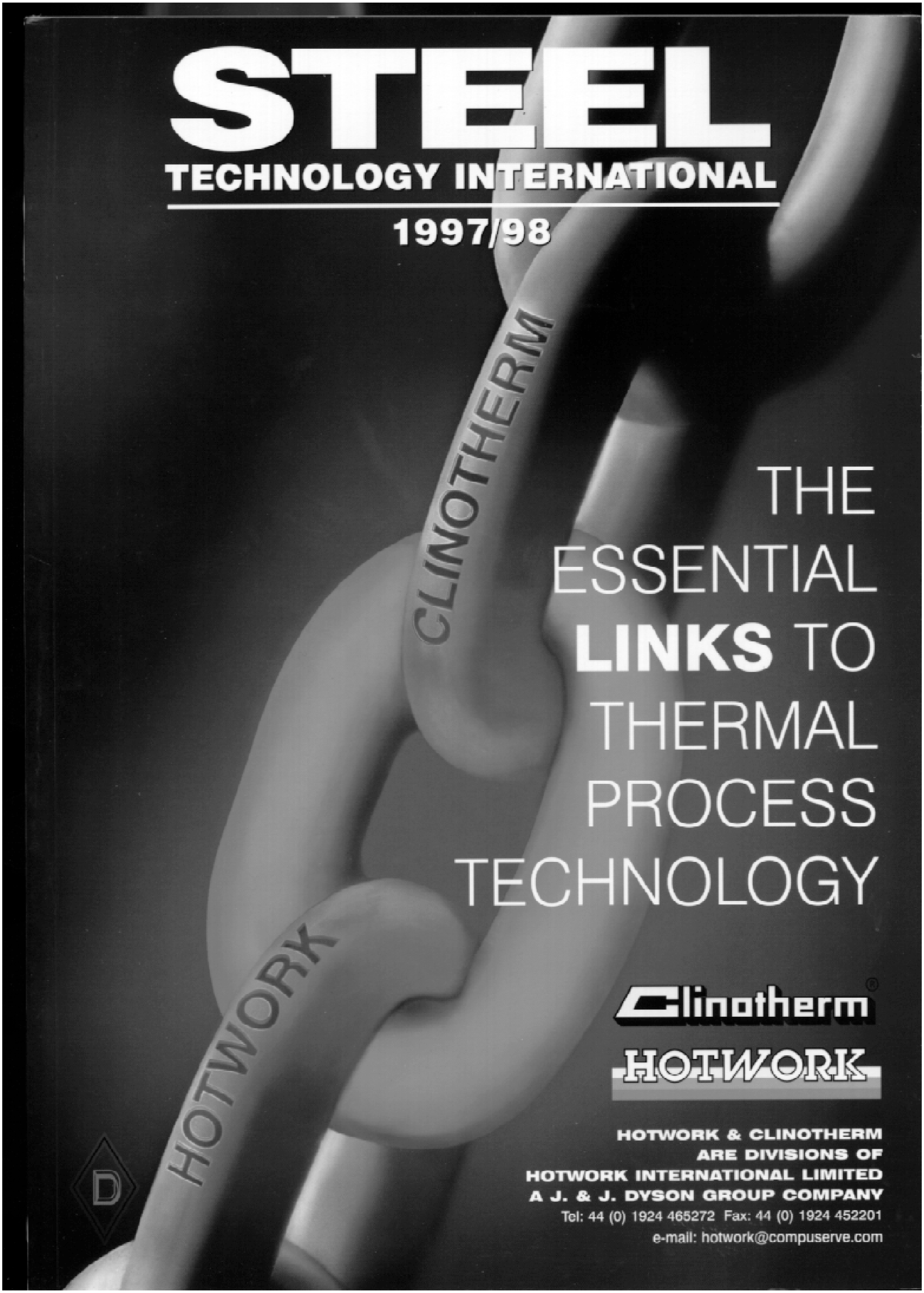

Adaptive profile optimisation for the EAF

Dr Edward Wilson of Neural Applications Corporation describes how the development of an intelligent adaptive system that will optimally control and co-ordinate multiple energy sources (selecting set-point profiles for electrical, oxygen, gas, and carbon energy inputs) is currently under way on the EAF at North Star Steel, Minnesota.

By applying artificial intelligence technologies such as neural networks to electrical power input control for the EAF, Neural Applications Corporation has achieved significant improvements in electrode consumption, electrical energy efficiency, and productivity.

A prototype is currently under development on the EAF at North Star Steel (NSS), Minnesota, that will extend this technology, providing automatic optimisation and co-ordination of all major energy sources, including electrical power, oxygen, gas and carbon. The intelligent adaptive system will modify energy input profiles on a continuous basis, based on production data and on an objective function specified by the steelmaker.

The basic approach is to develop a model that can predict furnace performance in response to variations in the energy input profiles. Unlike theoretical or finite element modelling approaches, the neural network model used here is developed with and continuously adapted to match actual production data. Once the model exists, the space of possible energy input profiles will be searched to optimise the specified objective function.

The eventual outcome of this research effort will be a new product for the steel industry, the Intelligent Total Energy Controller (ITEC), which optimises the energy input from each source (electrical, oxygen, gas and carbon) in a co-ordinated manner. This intelligent control system will automatically adapt to changing furnace conditions, equipment, practice, and scrap properties, continuing to optimise after the initial design is installed. The user-specified objective function may include the following: energy costs; throughput; electrode consumption; furnace wear; and emissions.

Co-operating with NSS in the development of this prototype, Neural has developed and installed data collection, analysis, and modelling systems at the 100t DC EAF at NSS. The system metrics and relative weightings in the objective function were selected based on discussions with the meltshop superintendent.

Intelligent systems

Control and optimisation of complex modern industrial processes often exceeds the capabilities of conventional control technologies. It is sometimes valuable to augment conventional approaches of linear control systems, multi-variate statistics, and linear signal processing with intelligent systems technologies such as neural networks, fuzzy logic, and genetic algorithms.

Intelligent systems technologies are often difficult to apply, however. Careful selection of how and where to apply them is often the most important step in developing an intelligent control or optimisation system. More information on this topic may be found on

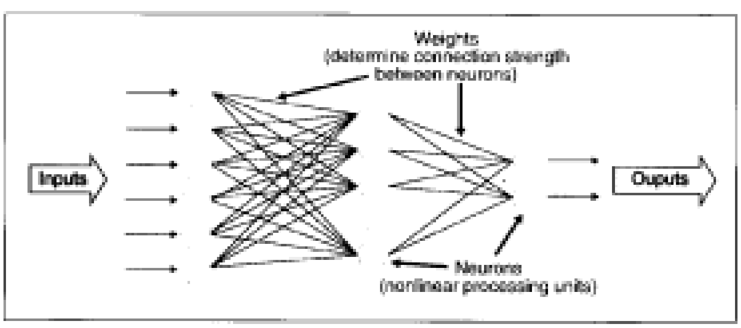

Figure 1. A simple neural network.

the Internet at http://www.neural.com.

The nonlinear, parallel, and adaptive capabilities of neural networks make them promising for control applications. Neural networks derive their advantage in solving complex problems from the emergent properties that come with the massive interconnection of simple processing units. With good training techniques, the networks are capable of implementing complex behaviours.

A simple example of a neural network is shown in Figure 1. The inputs (for example, sensors in a control application) enter at the left, where these signals are distributed to a number of nonlinear processing units (neurons) shown as the middle layer of circles. The outputs of these neurons are passed to another layer of neurons for output (for example, as control actuator values). This architecture, given sufficient number of neurons in the middle layer, is capable of implementing any multi-input/multi-output mapping. The neural network may be thought of as a generic nonlinear mapping function element. The functionality is defined by the gains (weights) of the connections between neurons. These weights are commonly set through adaptation, where the neural network is trained to emulate a given function, or a set of input-output data.

To determine where neural networks can contribute effectively, the control systems engineer must consider the strengths of neural networks (nonlinearity, adaptability, generality, ability to make parallel), as well as the costs associated with these benefits. The cost-benefit balance must be evaluated on an application by application basis.

EAF energy optimisation

The primary source of thermal energy in EAFs is the electric arc (65 per cent of kWh), with additional energy input from oxygen-fuel burners (5 per cent), and other exothermic reactions (30 per cent) that are supported by injecting oxygen into the furnace.[1] This oxygen combusts with carbon that is added as fuel, and with carbon, hydrocarbons, metals, and other elements already in the scrap. Currently, energy input set-point profiles are developed through trial and error, by simple linear algorithms, or are based on the experience of furnace operators.

As shown in Figure 2, 57 per cent of this energy ends up as heat in the molten steel. Ten per cent is lost as heat contained in the slag. Ten per cent is removed continuously by cooling water. Twenty-one per cent escapes through the off-gas vent ('fourth hole') in two forms: the hot gases represent a loss of sensible heat; and unburned fuel such as CO and H_2 is a loss of potential chemical heat energy. One goal of the research is to control and co-ordinate the energy inputs to reduce off-gas and cooling water losses, so that a greater proportion of the energy input is transferred to the steel.

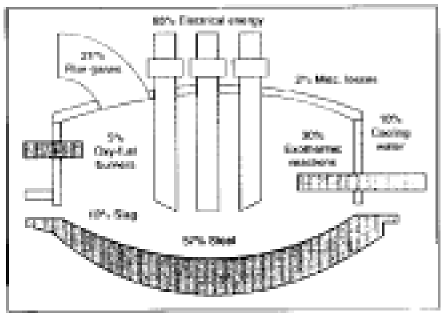

Figure 2. A furnace showing energy flow.

Of the major energy sources, Neural Applications Corporation has already achieved electrical energy savings of 2–8 per cent (also electrode savings of up to 25 per cent and throughput increases of up to 12 per cent) with the Intelligent Arc Furnace Controller (IAF(r)). The IAF uses patented neural network technology to optimise the regulation of the electrical input alone.[2,3] The 34 installations worldwide (26 in the USA), save up to \$1 million a year each in reduced energy costs, reduced electrode consumption, and increased throughput.

The time history of arc length set-points is commonly referred to as a "profile". Profiles are typically tuned manually according to the furnace operators' experience with the furnace. Optimisation of the arc length profiles in the IAF is currently achieved through manual tuning, a function that will be automated as part of this research.

There are similar input profiles for the oxygen lance and the oxygen-fuel burners. Standard practice is to use coarse profiles (off, low, or high flow rates) that are set according to operator experience. Optimising combustion inside the furnace is expected to yield comparatively better results than were achieved by the IAF for electrical optimisation. Owing to variance in the chemical makeup of the scrap, combustion is far from optimal, and a significant amount of unburned fuel is lost as CO exiting through the off-gas vent. The reaction from CO to CO_2 releases approximately four times as much energy as the reaction of C to CO. A gas analyser system for continuous monitoring of off-gas concentrations for CO, CO_2, and O_2 has been installed for use in profile optimisation and closed loop control.

ITEC development

The major steps in the development of the ITEC are illustrated in Figure 3. In the first phase of this research, a feasibility study was performed in which data acquisition and analysis systems were developed and installed on an EAF. The data was analysed over several months to validate the research approach, gauge the optimisation potential,

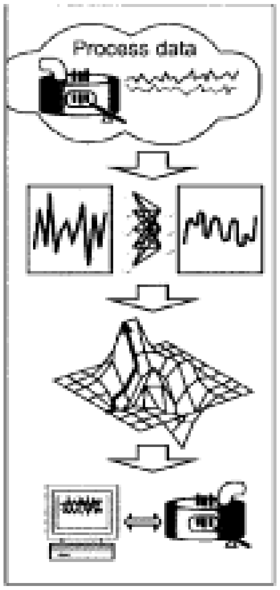

Figure 3. The development steps of the project, from data collection to control system implementation.

and further develop the modelling and optimisation strategy. Various intelligent technologies were investigated and evaluated after considering the characteristics of this optimisation application and the data collected. This methodology for evaluating and developing research projects is used in Neural's other research in the metals area.

The second illustration in Figure 3 represents the use of intelligent and conventional technologies to process the data, extracting the signal from the noise. In the second phase of this research, a cost function containing the variables and weightings specified by the steelmaker is evaluated for each heat. After evaluating this cost function for each of the thousands of heats we have logged, a neural network model can be developed that relates a concise input feature vector (describing energy inputs, and so on) to a predicted cost. As more data is logged and used to train a neural network model of the furnace operations, a model of the cost surface will be produced. A greatly simplified example of this concept is shown in Figure 4. The actual model will be far more complex, since each input will represent a dimension in the input space and the cost surface will be a multi-dimensional hyper-surface. This highlights the need for compression of the inputs into an input feature vector.

The model predicting total production cost as a function of oxygen input and electrical power on time (time during each heat when an arc is present) is plotted as a cost surface in Figure 4. All data is normalised by the weight of steel produced, and axis labels have been normalised. This figure demonstrates, for two input dimensions, the ability to develop a multi-dimensional production-cost model based on furnace data.

Once this surface has been developed, it may be searched (by many standard methods) to find the optimal set of inputs. This optimisation is represented in the third illustration in Figure 3. Hill-climbing will be used to determine different input conditions to try in experiments. Since each experiment takes about 90 minutes (one heat), it would be difficult to succeed with a genetic algorithm approach here. However, if the modelling proves sufficiently accurate, genetic optimisation could be attempted on a simulated system model.

When integrated into a GUI-driven system, the model will give production managers an opportunity to see what production costs would result from tweaking the input profiles — "what-if" predictive capability. The optimisation algorithm must be

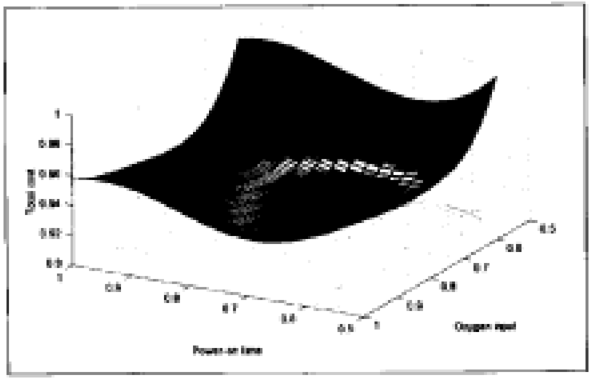

Figure 4. A representative cost surface used in optimisation.

constrained by limitations imposed due to safety requirements and equipment limitations.

After studying the optimisation capabilities that would best benefit the steelmaker, it was found that the ability to adjust the objective function was needed (primarily to account for varying energy costs or production throughput demands). The modelling and optimisation strategy was designed to permit quick changes in the cost function. Changes to the cost function will result in different multi-dimensional cost surfaces, but since the summarised data for each heat is stored, it will be possible to find the (estimated) new optimum very quickly. If the cost function remains at this new setting for some time, performance will be further optimised as more data is gathered in this new area. To account for the fact that furnace equipment, procedures, personnel, and scrap characteristics change over time, the relative weighting given to each data point will be exponentially decreased with its age. This will change the cost surface, and give the system the capability to adapt automatically to these process changes.

This strategy was based on:

- Neural's experience with the IAF and understanding of the steelmaker's needs
- Analysis of the noise level present in this complex industrial process, and
- Evaluation and comparison with several possible modelling and optimisation approaches (direct neural network modelling, genetic algorithms and so on). ■

References

1. Vonesh F A and Perrin N G (1995) "Post-Combustion for the Electric Arc Furnace". *Iron and Steel Engineer,* June 1995.
2. Staib W E (1993) "The Intelligent Arc Furnace", *Steel Technology International,* Sterling Publications Limited, London, 1993.
3. Bliss N G and Gilbertson G J (1995) "Neural networks for EAF power control". *Steel Technology International,* Sterling Publications Limited, London, 1995.

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