Process Modelling with Neural Networks

A computerized model of an industrial process is an invaluable tool for plant engineers and system designers. Now neural networks provide a simple alternative to conventional modelling techniques.

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Many computer methods have been used for the simulation and modelling of processes. Statistical time series methods, involving the empirical fitting of parameters to autoregressive moving average models is one of the common methods, but require considerable competence in statistical methods [1]. Another method of modelling is the analytical approach where the entire model is based on physical properties and a set of mathematical equations. The generation of these analytical models is extremely labour intensive and the models have to be fine-tuned by adjustment of certain built-in factors [2]. Other methods, including the generation of nonlinear empirical response surfaces, nonlinear regression, linear system identification, and fuzzy identification, have also been applied with varying degrees of success.

Neural network technology offers an alternative method for the generation of process models. The advantages of using a neural network to represent a system are its ability to perform a nonlinear mapping between inputs and outputs and the necessity of requiring minimal prior knowledge of the system.

The neural network

A neural network (or more correctly, an artificial neural network) is a man-made system imitating the neural structure observed in living organisms. Neural networks are mostly implemented as software programs running on standard PC hardware, but dedicated neural network hardware is also available. Like an animal brain, a neural network can learn complex nonlinear relationships, even when the input information is noisy and imprecise. A neural network is trained on a set of examples consisting of input patterns and desired output patterns. Once a neural network has been trained, it can produce outputs based on its inputs and prior training.

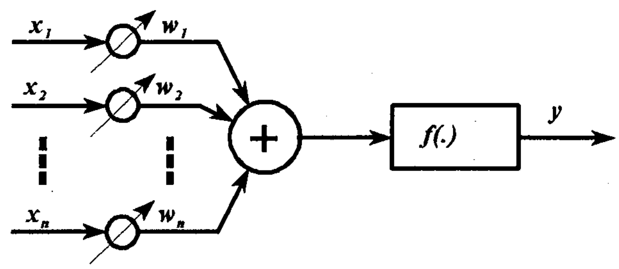

Figure 1 An artificial neuron.

A neural network is composed of many simple and similar processing elements called artificial neurons (Figure 1). A neuron receives data inputs from the external world or from other neurons. Each input is multiplied by an adjustable gain factor (called a weight) before being added together and passed through a limiting function. A sigmoid curve: $f(x) = 1 / (1 - e^{-x})$, is the most commonly used limiting function. The output of the limiting function becomes the output of the neuron. This output may be passed on as inputs to other neurons, or it may be an output of the network.

Neurons with no inputs and a constant unity output, known as threshold or bias neurons, are implemented in a neural network where a constant offset is required. Neurons of which neither the inputs nor the outputs are externally connected are called hidden neurons.

The neurons in a neural network are arranged in layers. Although some rules of thumb have been established, the number of neurons and layers in a network is mostly determined through trail-and-error. Figure 2 illustrates a neural network with three inputs on the input layer, two hidden layers with three neurons each, and an output layer with one neuron. The network also has a bias neuron in each layer. If the inputs to this network were temperature, pressure, and flow rate, for example, the network could be trained to model the energy flow rate at a certain point in a process.

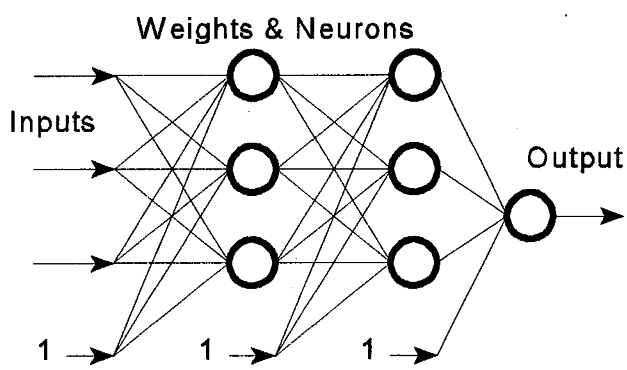

Figure 2 A small multilayer neural network.

Artificial learning

As mentioned, connections between the neurons in a neural network each have a certain internal gain called a weight. Changing the weight of a connection will alter the behaviour of a neuron, and therefore, it will also alter the behaviour of the entire network. The training of a neural network involves changing these weights so that the neural network behaves in the desired fashion. A technique called backpropagation is commonly used for training a network [3]. This technique adjusts the weights to minimize the squared error between the neural network's actual output values and the desired output values.

There is strong evidence to support that the learning mechanism of a neural network is simply a complex curve-fitting method that allows a network of simple processing elements to behave in a complex way. In fact, it has been proved that a neural network with at least one hidden layer has the capability to approximate any desired nonlinear function to an arbitrary degree of accuracy, given a sufficient number of neurons [4].

Modelling capabilities

The nonlinear mapping

capabilities of a neural network allow the creation of accurate models of nonlinear processes. For example, one of the most nonlinear industrial processes, being pH control in a neutralization tank, has successfully been modelled using a neural network.

The modelling capabilities of neural networks have also been applied as *inferential sensors* to obtain estimates of various process variables for which no easy method of on-line measurement exists. Also called *soft sensors*, these neural network based virtual instruments have been applied with great success to industrial processes, paper making machines, and power boilers, while user configuration makes these systems capable of inferring many unmeasured variables on-line.

The power plant boiler

One practical example of the application of a neural network model is the boiler heat transfer model created for Kendal Power Station. The objective of the heat transfer model was to provide heat pickup in the various boiler elements based on the conditions in the furnace.

A simplified diagram of the water/steam cycle used in power plant is given in Figure 3. Condensed water is pumped to the economiser where it is heated. The heated water is boiled in the evaporator while the steam is heated further in the super-heater. The steam expands through a high pressure turbine where its energy is converted to mechanical work. The steam is then reheated and passed on to the low pressure turbine to produce more work. Finally, the steam is condensed to complete the cycle.

During the combustion process inside the boiler, energy is converted to heat which is discharged into the furnace space. The heat is transferred to the boiler tubes through three individual mech-anisms: conduction, convection

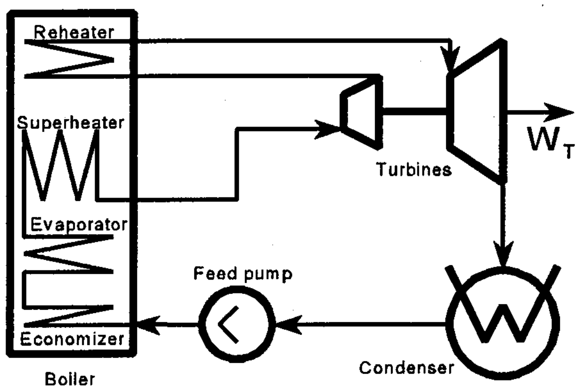

Figure 3. Power plant steam/water cycle.

and radiation. The heat transfer rate is dependant (amongst others) on the furnace flame temperature, the flue gas temperature, flue gas velocity and the geometry of the furnace and boiler tubes [5].

Modelling heat transfer

The boiler tube geometry and the layout of the various boiler elements are quite complex (see Figure 4) and this makes the application of analytical modelling techniques extremely difficult. Additionally, the heat transfer rate varies in a nonlinear fashion with boiler load, adding to the complexity of an analytical heat transfer model.

Creating a heat transfer model based on boiler heat transfer theory, is therefore an extremely complicated task. In most cases, the modelling accuracy is so poor that the model has to be calibrated against the real system to be of any use.

At Kendal, the shortfalls of conventional modelling techniques were eliminated by applying neural network technology to the problem. The shift in modelling technique

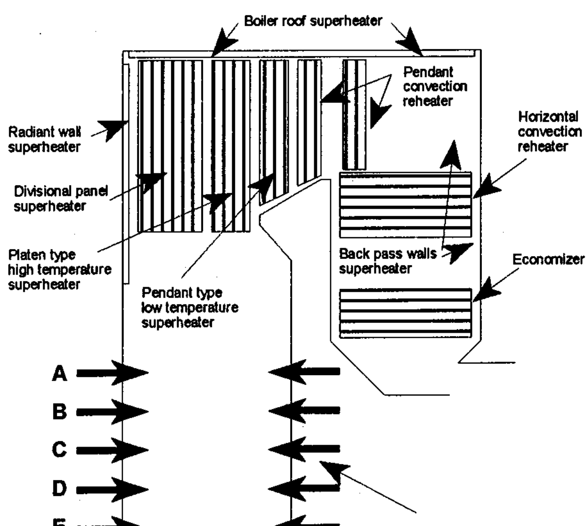

Figure 4. Typical layout of boiler elements.

was based on the excellent nonlinear modelling capabilities of neural networks.

A neural network process model may be created by following five steps:

a) Configure model inputs
b) Configure model outputs
c) Obtain training data
d) Determine network size
e) Train the network.

It may be necessary to repeat the last two steps while seeking for the optimum network size. The way in which Kendal addressed these points is outlined below.

Model inputs

Inputs to the model (seven in total) were chosen as the plant measurements having the largest effect on heat transfer rate. These were the individual mill (coal pulveriser) firing rates, O_2 in flue gas concentration, and burner tilt angle.

Model outputs

The network outputs are always chosen as the modelling objectives. These were configured to represent heat transfer rates to the evaporator, superheater, and reheater. The neural network outputs were later reconfigured to represent the heat transfer to each boiler element in relation to the total heat transfer, because this arrangement gave improved accuracy.

Training data

Training data was obtained from 128 tests specially designed to extract the heat transfer characteristics of the boiler. Ninety-five process values (pressures, temperatures, and flow rates) were recorded.

The individual mill loads, O_2 measurement, and burner tilt angle were recorded for each test and were used directly in the training data sets.

From the rest of the recorded data, the enthalpy of water/steam was calculated at 26 positions in the cycle for every test. Thereafter, the total heat transfer rates to the evaporator, superheater and reheater were calculated and these were used in the training data sets.

Training the network

The PC software package *Brainmaker* [6] was used to train the neural network on the test data. Ninety percent of the test data was used for training and the remainder was used to test the modelling accuracy (which is best tested with data not used in training [6]).

Network size

Various neural networks of different sizes were configured, each network was trained, and the results were compared on the basis of modelling accuracy. The network with seven inputs, fifteen hidden neurons and three outputs were found to be the best compromise between modelling accuracy and network complexity. The best modelling accuracy achieved was an RMS error of 2.8 % across all tests.

User interface

Once the neural network was trained, a user-friendly "front-end" were configured (Figure 5). A standard spreadsheet running on a personal computer was utilised for this purpose. The spreadsheet uses the trained neural network to calculate heat transfer rates based on inputs from a block of cells. The input cells allow changes to be made to mill firing rates, burner tilt angle, and O_2 setpoint. The inputs are passed on to cells doing the neural network calculations. The numeric values of the neural network weights were uploaded from a network configuration file created by the Brainmaker programme. The neural network outputs were configured to display the modelled heat transfer rate to the evaporator, superheater, and reheater.

Applications

The heat transfer model was originally used as part of a project on neural network control to explore the feasibility of the latter. It is now being used as an engineering tool for determining heat transfer rates under various furnace conditions. The model has also been used for optimization of control elements and for general "what-if" studies. The heat transfer model, which is quite easy to operate, has also been used by Matimba Power Station to test the feasibility of manipulating burner tilt position to minimize desuperheating spray water consumption.

References

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INPUTS			Min	Max
A-Mill demand	70.0	%	40	115
B-Mill demand	0.0	%	0	0
C-Mill demand	70.0	%	40	115
D-Mill demand	70.0	%	40	115
E-Mill demand	70.0	%	50	115
Burner Tilt Angle	15.0	deg	-30	30
O2 Setpoint	3.5	%	2.5	5.5
Fuel factor	1.05			
Coal CV	19.05	MJ/kg		
CALCULATIONS			Min	Max
Total fuel flow	89.4	%	0	120
Heat absorbed based on boiler efficiency	1398	MJ/s		
Heat discharged based on coal flow	1536	MJ/s		
Boiler efficiency	91.0	%		
Estimated generator load	613.0	MW		
MODEL OUTPUTS			Target	RMS err
Heat Tx to economiser and evaporator	678.2	MJ/s	601.2	116.1
Heat Tx to superheater	463.0	MJ/s	398.2	
Heat Tx to reheater	256.7	MJ/s	198.8	
Total heat Tx to boiler elements	1397.9	MJ/s		
ESTIMATED ERROR				
Error on uncorrected total heat transfer	0.1	%		

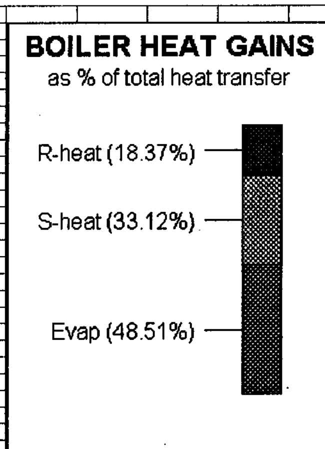

Figure 5. The neural network boiler heat transfer model running on a spreadsheet.

Jacques Francois Smuts has seven years of experience in process control and is currently working for Eskom. He was awarded B.Eng and M.Eng degrees at the Rand Afrikaans University and has recently completed his Doctorate thesis on the application of neural networks to steam temperature control on power plant boilers.

Andre Leon Nel is an Associate Professor in Mechanical Engineering at the Rand Afrikaans University. His primary research interests include the use of neural networks for modelling nonlinear phenomena and the effects of modifying training parameters of such networks on their ability to generalize the characteristics of the parameter space.