Intelligent Control System for Ferroalloy Plant Using Expert System and Neural Networks

B. Z. Livneh and X. Pan

Knowledge Based Engineering (Pty) Ltd.
3rd floor, Corporate Place, 23 Fredman Drive, Sandown, Sandton 2146, South Africa

ABSTRACT

Opportunities for maximising corporate revenues through plant-wide intelligent control are being considered in ferroalloy plants world-wide. Ferroalloy processes are typically large scale, multistage, multiple-variable, non-linear, with long-time delays, high reaction rate and usually unstable operations. The relationships between the process variables and operation parameters are complex and difficult to predict using traditional process control and modelling techniques, which requires a fresh approach to automation.

Artificial intelligence techniques such as expert systems and neural networks have been utilised and proved to be beneficial not only in understanding the behaviour of the processes but also in intelligently controlling the operation in terms of prediction and optimisation.

Gensym™ G2 ® real-time expert system and Pavilion"! Process-Insights * neural networks have been used together to develop an intelligent control system to control a ferroalloy plant in South Africa. The architecture and functionality of the system and the reasons why expert systems and neural networks are needed for the intelligent control system are discussed. Some of the results achieved by using the intelligent control system are illustrated specifically. The advantages and limitations of the intelligent control are briefly highlighted.

1. INTRODUCTION

One of the most important requirements in ferroalloy production is to maintain a high stability of furnace operation. A ferroalloy plant usually consists of four systems:

- raw materials handling,
- submerged arc furnace,
- gas recovery,
- utilities.

The submerged arc furnace used in the production of ferroalloy is a very complicated unit operation, in which solid, liquid and gaseous phases coexist. The physical and chemical processes that are taking place inside the furnace include heat transfer, oxidisation, reduction, material melting and gas generation.

Due to the ill-understood slag/metal behaviour, very high temperature and thick brick wall it is impossible to measure many of the critical process variables directly. Hence, internal process conditions indicating current furnace behaviour, such as temperature and composition of slag/metal have to be inferred. Other difficulties in controlling plant production could be summarised as follows:

- process non-linearity;
- ill-understood first-principles of physical and chemical mechanisms;
- highly inter-reactive process parameters;
- inherent variability of process time-delays;
- inadequate and uncertain measurement;
- the need to incorporate process safety and environmental considerations;
- time lags between sample taking and lab results;
- unstable external variables such as feed-stock composition, ambient temperature and pressure, etc.;
- link between process parameters and cost of production.

Due to the difficulties in understanding and controlling the complicated systems, actual production depends largely on the 'gut-feel' knowledge and intuition of experts who have many years of experience in the production and plant operation. These experts estimate the furnace operation conditions on the basis of information obtained from hundreds of plant measurements via a traditional supervisory control system, and take appropriate actions according to the estimated operating conditions of the plant.

2. Knowledge Representation

The task of performing intelligent process control is complex, and requires capturing, handling and manipulation of operational and theoretical knowledge. Generally speaking, there are two sources of working knowledge:

- **Intensive knowledge**: a detailed knowledge of the internal forces acting on the furnace, including operational knowledge. This knowledge is termed **'know-how'**, and includes causal knowledge of the how process variables affect each other. This knowledge could be represented in a set of mathematical equations, or a set of operational rules.
- **Extensive knowledge**: in the case of ill-understood processes, the intensive knowledge is unavailable. In this case historical data of past operation must be used to gain plant knowledge. This knowledge is called 'know-what' and is the other source of knowledge, i. e. knowledge gained from intelligent observation of the process.

The combination of these two sources of furnace knowledge are combined together to produce an integrated and knowledge intensive plant model. This model incorporates the combined knowledge of the furnace operation, and runs in parallel to the process, and seen in the following drawing:

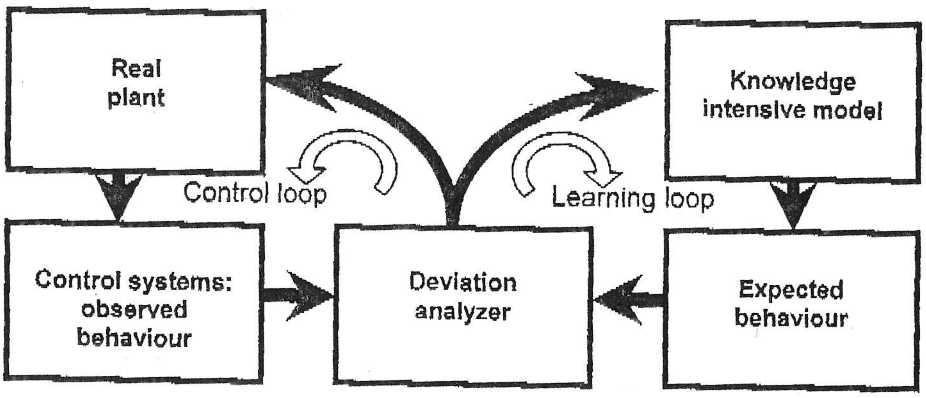

Figure 1: Intelligent control system block diagram

In figure 1, the real plant'S performance is continuously measured by its real time data collecting devices such as PLC, DCS, etc. The collection of real time data is called the '**observed behaviour'**, which represents the data that tells the system what is happening in the furnace at any given time.

The knowledge intensive model is a detail representation of plant knowledge using neural network techniques for data analysis and expert system techniques for operating rules in an integrated fashion. This model runs in real time and in parallel to the process. It continuously generates what is called '**expected behaviour'** - i. e. the behaviour patterns that the human expert expects the furnace to perform.

In the case of deviation, i. e. when expected behaviour of the furnace does not comply with its observed behaviour, a deviation analysis is being performed to identify the correct response to this deviation. The result is a recommended control command suggesting a change to the furnace operating conditions (such as setpoint change) that is sent back to the furnace, and represents the control loop.

The user may decide to deploy the suggested command or ignore it, as the system in its current configuration serves in an advisory mode. However, as trust in the system builds up, it is designed to operate in a totally automatic fashion.

In some cases expected behaviour and observed behaviour do not correlate; not because the real plant is misbehaving, but rather because the model is incomplete. In such cases a command is sent to the model to change (or update), and this is the learning loop. Neural network technology is suitable for such tasks, and real time, on-line network training is a well-developed technique.

An intelligent process control system that is following these principles has been developed and deployed by KBE for a ferroalloy smelting furnace at one of the furnaces in a leading South African firm. The knowledge intensive model employed consists of a Gensym"! G2 * real-time expert system for operation rules and intensive furnace knowledge, and Pavilion"! Process-Insights * neural networks which capture the extensive furnace knowledge.

3. EXPERT SYSTEM

The operational know-how and knowledge gained by expert operators is captured and represented in an expert system. In this case, the off-the-shelf Gensym"! G2 * real-time expert was selected. The Expert system portion of intelligent process control can only be applied when operational knowledge can be logically represented in a cause / affect manner or in a mathematical form.

For example, a situation when air is leaking into the furnace can be represented by two rules:

- the rate of change of the furnace roof temperature over a certain period of time,
- the recent change in the average value of CO/CO2 ratio of the furnace off-gases.

By continuously measuring the data and invoking these rules the expert system is able to detect the ingress of air into the furnace. When this situation is detected, the expert system makes the operator aware of the situation and advisees him/her of the most appropriate actions to follow.

Some actions could be to validate the situation, such as the following message:

"air is leaking into furnace, please check the air-sealing around the furnace and report to the production engineer".

In more sever cases the system may even suggest to switch the furnace off. The process, which the system performs automatically, is very similar to that the human operator performs, and includes:

- data reading,
- data manipulation,
- inferencing,
- reasoning and judgement,
- propose control commands.

In practice, the expert system rules dealing with air leaks are hard coded, and are using English-like rules. These rules are structured so that any production personnel can view them and maintain them.

4. NEURAL NETWORKS

The air-leaking example above makes use of causal knowledge that ties many process variables and timing together in a certain relationship. This knowledge is ideally dealt with in an expert system, and is known as 'temporal reasoning'. However, expert systems cannot be applied to knowledge that cannot be represented logically or in a causal relationship, or if these relationships are unclear.

Furnace operation requires knowledge of its internal process conditions. The immediate knowledge of metal composition and metal/slag tonnage, or better still, production costs, is critical to optimised furnace operation, and in most cases is not readily available. These types of variables could either be measured externally to the process, for example laboratory analysis, which introduces major delays in making them available, or cannot be directly measured at all. These process variables could then be inferred on from other ones that are easier to measure on line.

As mentioned earlier, the relationships between the internal furnace operating variables and the measured process parameters are not well understood. The only way to quantify these relationships is to examine the history of past operation. Neural networks proved to be an efficient tool for such a task.

Conceptually, first principle models are most appealing to predict furnace operating conditions. Such models are based on applied science like mathematics, chemistry and thermodynamics. Such models allow the user to obtain a good insight understanding of the process, and one can safely extrapolate new operating conditions not yet experienced. However, even when applying broad simplification assumptions, this approach requires a great deal of processing time and high level expertise to develop, and may not guarantee success.

While the analytical approach gained wide acceptance, it was faced with tremendous difficulties. Developers resorted to statistics, and developed statistical models of furnace behaviour. However, statistical modelling requires specialised knowledge of both statistical methods and process understanding, and by-and-large suffers from the limitation of linearity (i. e. a linear representation of a non-linear world)[1,2].

With the emergence of neural network technology, a new avenue became available to the industry, for developing high fidelity process models that are data driven. In this approach, the model uses existing historical data to gain insights into the process dynamics. Neural networks proved to be a very successful approach for model building, to predict and control the behaviour of many manufacturing processes[3-16].

Artificial neural networks[11,12,13] represent a set of powerful mathematical techniques for modelling, control and optimisation that "learns" processes dynamics directly from historical data.

In figure 2 above, there is a ferroalloy process that has multiple inputs (such as raw material, temperature, composition, slag basicity, etc.), with one or more desired output target functions (such as production cost, plant profit, power consumption, etc.). The output target function could be referred to as key performance indicators, which need to be predicted and optimised, and so define the success (or otherwise) of the process.

The neural network model learns the process dynamics from historical data so as to predict the desired outputs that closely match the actual outputs.

An important function of intelligent control systems is to know how to set controllable input variables, in order to achieve desired output targets by referencing other controllable input variables. This can be done by the setpoint capability of the neural network model. By fixing a desired values for the output target functions, the model will generate an optimised setpoint solution for the input variables under the current operational conditions, which is coupled with the knowledge of the sensitivity of the specific outputs to each input parameter.

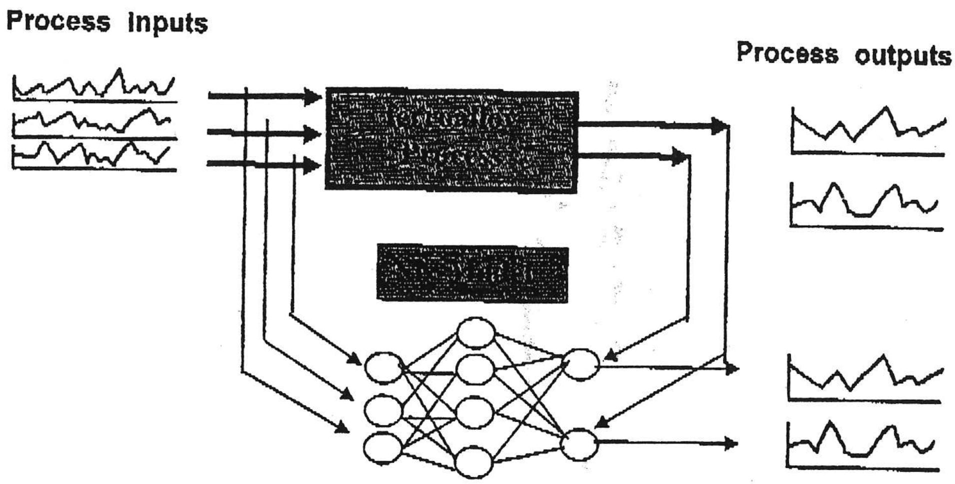

Figure 2: Neural network control model

A neural network model is another form of data abstraction. This data abstraction could then be used by the operator and be integrated with the expert system for further manipulation.

In its basic form, a neural network model could be used to predict key performance indicators from a set of input data. Process Insights * has a few unique advantages that make it an ideal tool for process control:

- The basic assumption of a typical neural network (and any statistical analysis for that matter) is that the input vector has no interdependencies between its various parameters. This is not the case in process control, where there is a great deal of interdependency between many of the input vector's parameters. For example, there is a critical dependency between steam flowing into a heat exchanger and the pressure difference across the heat exchanger. Process Insights deals with this in a novel manner, by simultaneously training two networks: one to de-couple the interdependencies of the input vector, and another one to predict the outputs.
- A normal network deals with instantaneous mapping of the input variables to the defined outputs. However, in process modelling one needs to take cognise of the fact that there are internal process time lags. Here too, Process Insights can deal with the fact that each process variable may have a different time lag (or time lead) between the time a disturbance is introduced to an input and the time it is manifested itself in the output variable.
- The most common task of a neural network model is to predict new outputs from a set of inputs. However, while prediction on its own is very useful, optimisation is what one keeps in mind when talks about intelligent process control. For this reason Process Insights model can be inverted, and from setting output requirements it can be used to predict inputs (setpoints) to achieve these requirements.

Advantage of Neural Network Model

Neural network "learns" a full non-linear high-dimensional response surface of the process dynamics from the process data of the plant. Neural network uses very simple functions in the hidden layers (typically sigmoidal), but it combines these functions in a multiple-layer nested structure, and it has been shown that any function can be approximated by neural network[1]. More details on the use of neural networks and the back-propagation algorithm could be found in the articles[11,13,14]. The major advantages of the neural network approach to the processes related to ferroalloy processes can be drawn as the following:

- The model requires little human expertise; the same neural network algorithm will work for many different systems[1,15],
- The model allows for a non-linear, more realistic

model;
- The model can achieve much more accurate results than traditional model techniques for complex processes (namely first-principles and statistics)[1,15,16];
- The model is relatively insensitive to typical process noise[1];
- Model execution is very fast.

Limitations of Neural Network Modelling Approach
Neural networks could be viewed as universal approximators to many different problems. It is tempting, therefore, to mistakenly view the neural network approach to the metallurgical processes as a panacea[2]. Neural networks represent, in some sense, a revolutionary approach to multiple-dimensional non-linear modelling in order to predict and control typical ferroalloy processes. At the same time, neural networks share the same limitation as any empirical or regression modelling techniques would have. The main limitations of using neural network models can be summarised:
- require large amount of data to build a model (as a rule of thumb, data point for each variable is 50 times of the total variables including inputs and outputs)[15];
- limited in their validity to the regions of data used to build the model
- no direct causal relationship the actual process could be drawn from the model;
- the model is only valid for the regions of the data used for its training. No extrapolation outside of these limits is of any validity;

5. PLANT OPTIMISATION

The big challenge in optimising plant operations is not only to quantify a production mode that can yield better business results, but also how to get from the current production mode to the more optimised mode. In many cases the actual route one takes in moving to the more optimised operating position can be more important than identifying that position itself, for the following reasons:
- One needs to make sure that in moving on the route to an optimised operation, one does not compromise safety procedures;
- That the route is not producing off-specifications products;
- That the route does not produce by-products which are environmentally hazardous;
- That the route is not a lengthy one, but rather faster than the internal process dynamics;
- That the destabilising the operation.

All of these and other considerations need to be continuously evaluated. In this case, the novel approach of combining neural networks with expert systems provides with a great deal of benefits to the user.

Neural networks are very efficient in identifying process gains, and producing steady-state optimisers. In this case, the expert system was programmed with many production and safety rules that interfaced with the neural network model to capture some of the operation dynamics rules and constraints.

Generally speaking, intelligent control can have two modes of operation: it can perform a close-loop automatic control, or open-loop in and advisory mode. When in advisory control, the system's task is to advise a human operator who must use operational judgement in accepting or rejecting the system's recommendation. In a close-loop operation, the intelligent control system will automatically deploy a control strategy deemed fit for the current process circumstances.

In both modes, the intelligent control system evaluates the situation and continuously monitors the plant's performance. In our case the system was designed to close the loop, but in the initial stage it is used in an advisory mode. Any control strategy is suggested to the use through an intelligent man-machine interface (MMI) component, which handles system messages and guides the user through the process.

6. PRACTICAL ISSUES IN BUILDING NEURAL NETWORK MODEL FOR FURNACE INTELLIGENT CONTROL

The Smelting Process
The smelting process used for ferroalloy production includes five types of variables, which are classified

as inputs of the processes:
- raw material information;
- electrical utility information;
- electrode/blown gas information;
- refractory information;
- coolant information.

The outputs of the processes includes the following:
- metal-mass;
- metal-composition;
- metal-temperature;
- slag-mass;
- slag-composition;
- slag-temperature;
- gas-volume;
- gas-composition;
- gas-temperature.

In addition, other variables are usually used to evaluate process economics. These include:

- electricity consumption (kWh/ton);
- raw material consumption (t/ton):
- electrode consumption (kg/ton):
- refractory consumption (kg/ton)
- production cost ($/ton);
- production profit ($/day);
- Production rate.

Software Configuration
The software products used for the intelligent control system are as the following:

1. Gensym G2 expert system;
2. Pavilion run-time software controller (RTSC);
3. bridge between G2 and RTSC
4. bridge between G2 and the DCS
5. bridge to LIMS (lab information system)

In order to run the neural network model on-line, the RTSC had to be implemented. This software runs the furnace neural network model, and supplies both the prediction of parameters which cannot be measured, and the set-points for the controllable input variables of the process.

The expert system is able to communicate with the RTSC via a specially designed software bridge. Another software bridge supplies the transfer between expert system and the plant Moore DCS. The bridge between the RTSC and a database is required when the neural network model needs to be trained online. The relationship between Process Insights, the run-time software controller (RTSC), the G2 expert system, the DCS and the plant is illustrated in figure 3.

Control Functions
The functions of the intelligent control system can be briefly summarised as the following:

- Production-cost optimisation
- Process prediction
- Operation advisory
- Intelligent alarm
- Event management
- Result display
- Report management
- System security

7. PROJECT EXECUTION

The initial phase of the project was to develop a neural network model of the furnace based on available operation data. The role of the model was two folds:
- To serve as a proof of concept to ensure that a technology solution could work for a complex furnace control;
- To quantify potential saving which can serve for financial justification for the entire project.

During the first phase of three months, a good model was built which shows that potentially the client could reduce production costs by up to 30%(!). The road was then opened for a full implementation of the system.

The neural network run during the latter half of 1997 has provided better than expected accuracy. R-squared (Co-efficient of determination) for the model was 0.887, which implies that 88.7% of the variance of the furnace's output is predicted by the model.

A sensitivity analysis was then conducted, giving the influence of every input parameter on each output parameter. The different inputs are sorted in a priority order for individual output, so that the most important ones are immediately identified. This provided us with an indication where to concentrate our efforts to maximise the return. The most sensitive process variables were given priority in defining and implementing an intelligent control strategy.

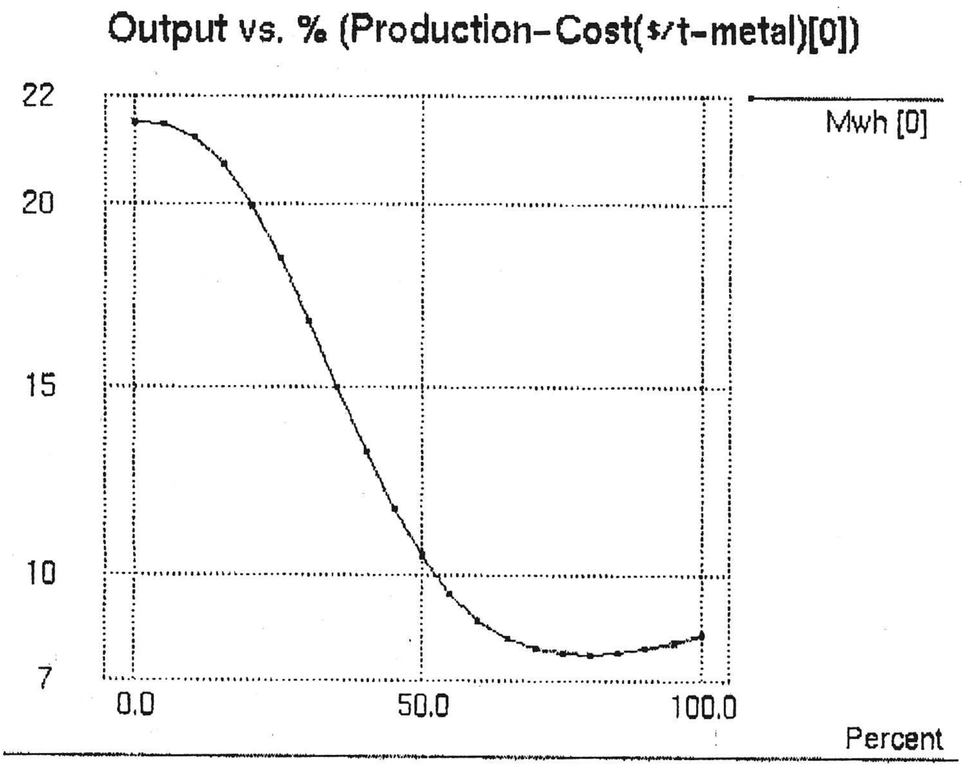

Figure 3: Dependency between power consumption and production costs

In this phase some interesting and surprising results were detected. For example, figure 3 above shows how power consumption influences total production costs (please note that the original figures are hidden).

Sensitivity is defined as:

$$Senitivity = \frac{\partial out_k}{\partial in_k}$$

Sensitivity of output versus certain input is not constant across the total range of the data set. In principle, there are four possible types of sensitivity analysis between any input an output:

From the drawings above it is evident that the relationship between power consumption and production costs is non-liear, non-monotonic. This meas that the prediction of the of power consumption on production costs is very situational. Furthermore, control over such a relationship is very complex and could not be achieved with traditional techniques such as PID. Power consuption and other parameters which display similar behaviour are mostly controlled manually, and hence achieve sub-optimum conditions.

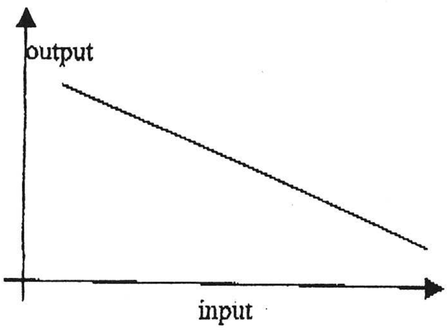

Figure 3: linear relationship

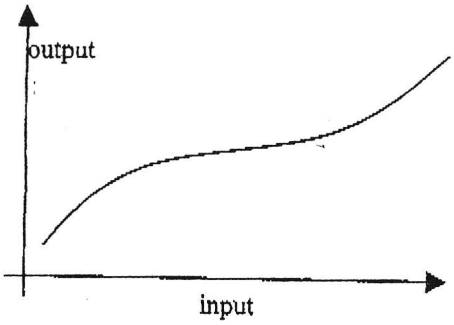

Figure 3: non-linear, monotonic relationship

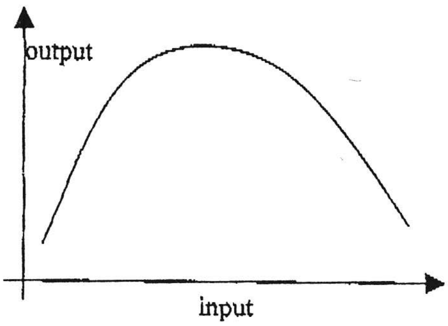

Figure 3: non-linear, non-monotonic relationship

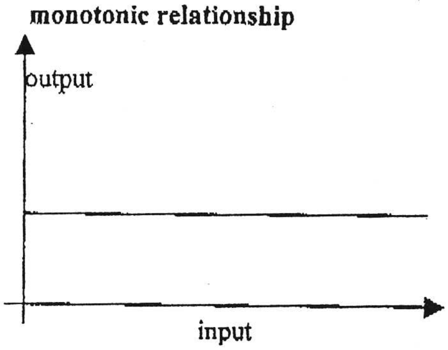

Figure 4: no causal relationship

What-if Analysis

What-if analysis allows the user to simulate different operating conditions without disturbing the plant. It is easy to investigate the effect of changing one or several inputs on the outputs by running the model in prediction mode.

Process limitations such as hard constraints, rate constraints, and fuzzy constraints were imposed upon each independent input and dependent input in accordance with the actual plant operational environment. The consequent affect on the output parameters was investigated.

Rate constraints are specified as non-negative numbers that limit the variable's rate of change, that is, how far in each direction a recommended set-point result is allowed to differ from the variable's initial value.

Fuzzy constraints specify undesirable regions that the solution should avoid if possible, but which can be transgressed, if necessary.

The model will never produce a solution that violates hard constraints and rate constraints. It will always try to find a solution that satisfies the specified fuzzy constraints, but it may be that no such a solution exists. In the later case, the "best" solution will be one that least violates the fuzzy constraints.

8. SYSTEM DESIGN PHILOSOPHY

The design philosophy that was adopted in this project was as follows:

- The system is designed not to duplicate the existing process control and supervisory system, which is in this case was a Moore DCS.
- The system was designed to be a supplement to the DCS in that it is linked directly to the process control network and reads real time process data directly from the furnace's data logging facilities. However, it does not include any traditional control function such as interlocks, PID loop control, normal alarms, etc.
- The system is designed to have the capability of operating in an advisory mode (open-loop) and automatic mode (close-loop).
- In an advisory mode, the system includes powerful man-machine interface that automatically navigates the user through changing screens of process

diagrams and detailed instructions as to what needs to be done.

- The user can override the system at any time. While this is done, the system logs its recommendations and the operator's actions to special reports. These reports are then used for auditing the system's performance as well as the operators * reactions. This is done to continuously improve on the system's performance and operators * acceptance.
- Facilities are included to automate routine functions such as start-up and shut-down. These procedures are designed to be entered and maintained by production personnel, with minimal interaction with system engineers.
- It was envisaged that there would be a need to more than one neural network model to capture the breath of furnace operation knowledge. For this reason, the system is designed so that as many neural networks model as needed could be integrated. For example, the same model is trained on 24-hour data and 1-minute data. Each model address different furnace dynamics for different use. The 24-hour model is used more to optimise long term financial issues while the 1-minute is used to identify dynamic changes to the furnace operation.
- The expert system portion is loaded with plant operational knowledge that was obtained from production experts in an extensive knowledge elicitation phase. This knowledge is running along side the neural network models, and invokes the relevant model as and when it is needed.
- The extensive man-machine interface that is used for communicating plant conditions and recommendations to the operators is using expert systems technology. This provides for intelligent guidance of the operator through the process complexity, and is simplifying the complexity of the intelligent control system.

9. CONCLUSION

The combinations of neural networks and expert systems have major benefits in controlling ill-understood processes such as ferroalloy production. It helps in predicting events, controlling costs and guides the users to more optimum conditions.

Such a project requires total commitment and dedication from operation management, and full participation of the operating personnel in the diff ent phases of the project.

Some of the important lessons learnt:

- Always select a mechanically stable furnace to deploy intelligent control on. Unstable furnace shifts the focus of the operators to other issues, and reduces the observed benefits.
- It is recommended that an intelligent control system becomes an integral part of the control system. This is quite simple to achieve in a green field case, but may be more difficult in a brown field case.
- It is highly recommended that the supervisory system (the screen the operators use) become the same for the standard control and the intelligent control to achieve maximum benefits.
- Although an intelligent control system is not a mission critical one, it is recommended to build it with high availability function. This investment may support (and in cases of failure) substitute the control system.
- It is quite easy to fall into a trap and train neural network on process noise, which is quite high in ferroalloy processes. Special care must then be given, and the models must be well validated before deploying it in a control system.
- The rule base development must involve to management as well as operational staff. A few good rules are better than many poor ones.

REFERENCE

1. Keeler, J. D. (1993). Prediction and Control of Chaotic Chemical Reactions via Neural Network Model, 1993 Conference on Artificial Intelligence in Petroleum Exploration and Production (CAIPEP), Plano, TX, May 19-22,1993, pp1-7;
2. Unger, L. H, Eric, J. H, Keeler. J. D and Martin. G. D. (1995). Process Modelling and Control Using Neural Networks * Reprinting from the Proceedings of the Intelligent System in Process Engineering Conference (ISPE) Snowmass, CO, July 1995, pp1-11;
3. Pan, X. W. (1996). Control Model for internal

use via Neural Networks, Project Report 1, October 6, 1996, pp1-42;
4. Pan, X. W. (1996). Advanced Control of a Ferroalloy Plant by using Pavilion Neural Networks and G2 Expert System, Project Report to customer, November 7, 1996, pp1-19;
5. Spangler, M. V. (1994). Uses of Process Insights at a Refractory Gold Plant, Pavilion Users Conference, October 17, 1994, pp1-7;
6. Tatsuro, H, Kozo. Y, Shinobu. M, Hiroshi. T. (1990). Blast Furnace Operation System Using Neural Networks and Knowledge-Base, Proceedings of the Sixth International Iron and Steel Congress, 1990, Nagoya, ISIJ, pp23-27;
7. Karl-Heinz, P, Ernst, W, Wolfgang. K, etc. (1990). Modern Blast Furnace Facilities at Thyssen Stahl AG, Proceedings of the Sixth International Iron and Steel Congress, 1990, Nagoya, ISIJ, pp16-19;
8. Inkala, P, Karppinen. A, Seppanen, M. (1995). Computer Systems for Controlling Blast Furnace Operations at Rautaruukki, Iron Steel Eng. , August 1995, 72,(8), pp44-48;
9. Pegden, C. D. (1993). Simulation in the Steel Industry: Past, Present and Future, Proceedings of the Conference on Computerised Production Control in Steel Plant", Seoul, South Korea, November 1-5, 1993, pp11-18;
10. Saito, T. (1989). Application of Artificial Intelligence in Japanese Iron and Steel Industry, Proceedings of the 6th IFAC Symposium Automation in Mining, Mineral and Metal Processing, Buenos Aires, Argentina, September 4-8, 1989, pp31-38;
11. Hartman, E, Keeler, J. D and Kowalski, J. (1990). Layered Neural Networks With Gaussian Hidden Units as Universal Approachors, Neural Computation, 2, (1990), pp210-215;
12. Miller, W. T, Sutton, R. S and Werbos, P . J. (1990). Neural Networks for Control, MIT Press (1990);
13. Narendra, K. S, and Parthasarathy, K. (1990). Identification and control of Dynamic Systems using Neural Networks: IEEE Transactions on Neural Networks 1, (1990), pp4-27;
14. Rumelhart, D. E, Hinton, G. E and Williams. R. J. (1986). Learning Internal Representations by Error Propagation, Parallel Distributed Processing, *Explorations in the Microstructure of Cognition*, Volume 1, MIT Press/Bradford (1986);
15. Fortpied, A and Heymans, L. (1995). Neural Networks to Control an Alpha Olefin Plant, Honeywell Users Conference, Nice, France 1995;
Pavilion Technologies, Inc. (1995). Process Insights User's Guide, Version 3. 2. 1995 pp34.

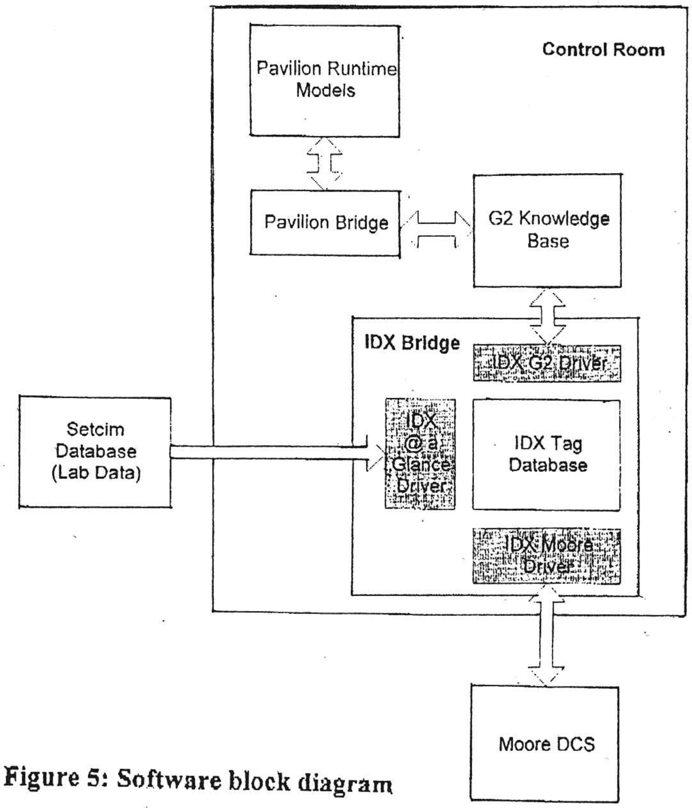

Figure 5: Software block diagram