Improvement and optimisation of hot dip galvanising line using neural networks and genetic algorithms

F. J. Martínez-de-Pisón*[1], F. Alba-Elías[1], M. Castejón-Limas[2] and J. A. González-Rodríguez[3]

In the present article, an application is present based on the combination of genetic algorithms and neural networks, used to improve the annealing process of a hot dip galvanising line with steel coils. The main objective is to determine the best settings for a furnace in order to reduce the margin of error between the actual strip temperature and expected temperature, not only for each coil that forms the strip, but also in the zones of the strip where transitions are formed by coils with different dimensions or steel types. Basically, the methodology consists in training a multilayer perceptron (MLP), which then determines the settings of the furnace and the speed of the strip according to the type of coil that forms the same strip. Another MLP is used to predict the dynamic behaviour of the strip related to its fluctuations in speed, as well as the temperature of the furnace. In this way, using simulations and genetic algorithms, the optimum settings of the furnace are determined, as well as the speed of the strip in those zones where there are changes in the coils, namely, in dimensions and types of steel.

Keywords: Neural networks, Hot dip process, Genetic algorithms, Improving industrial process

Introduction

The constant search to improve product quality and to reduce the costs of production is of primary importance in any industrial plant. One way of effecting these objectives is based on efficient methods and tools for data mining; an artificial intelligence that, by means of analysing historical data, helps in understanding the industrial process more completely and in developing strategies that lower costs, improve product quality and increase production.

In large steel and iron companies, one product of great interest (in terms of reducing cost and increasing quality) is steel, coated in an immersion process using a bath of liquid zinc. This product, known as 'galvanised steel', is used frequently in sectors such as car industry, electric household appliances and construction, owing to its excellent anticorrosive properties.

Hot dip galvanising line (HDGL)

A continuous, hot dip galvanising line is composed of several stages (*see* Fig. 1). The initial material is steel coil from the cold rolling with required thickness. It is unwound and runs through a series of vertical loops within the furnace. The temperature and cooling rates are controlled to obtain desired mechanical properties for each steel type. Figure 2 represents the thermal treatment that each steel coil has to undergo in an annealing furnace. This treatment is essential to improving properties of the strip and its coating.

Afterward, the steel strip runs through a molten zinc coating bath followed by an air stream 'wipe' that controls the thickness of the zinc finish. Finally, the strip passes through a series of auxiliary processes, forming a coil shaped product.

Quality of galvanised product

The quality of the galvanised product, according to various authors[1–6] can be assessed by examining two fundamental aspects:

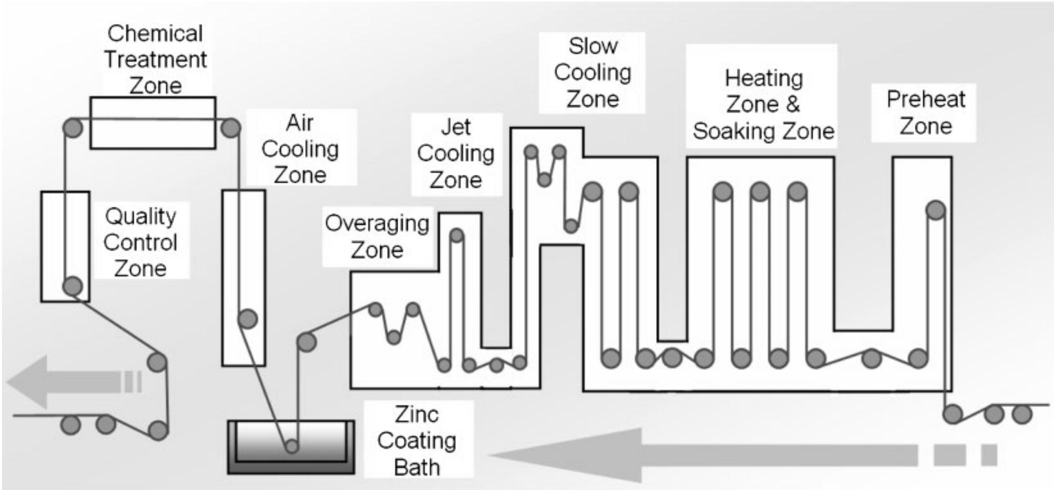
(i) in terms of the anticorrosive characteristics, determined by the thickness and uniformity of the zinc coating, which depend basically on the surface preparation of the metal base, the control and homogenisation of the zinc coating, the composition of the bath, the control of the air currents and the speed of the strip

(ii) in terms of properties of the steel, depending fundamentally on the composition of the steel, smelting process, rolling process, lamination processes and heat treatment performed on the strip before its immersion in the liquid zinc bath.

[1]Área de Proyectos de Ingeniería, Universidad de La Rioja, C/Luis de Ulloa 20, 26004, Logroño, La Rioja, Spain
[2]Área de Proyecto de Ingeniería, Dpto. de Ingeniería Eléctrica, Universidad de León, León, Spain
[3]División de Innovación e Investigación, Aceralia, Grupo Arcelor, Avilés, Spain

*Corresponding author, email fjmartin@dim.unirioja.es

Published by Maney on behalf of the Institute
Received 10 May 2004; accepted 13 January 2006
DOI 10.1179/174328106X101565



1 Basic scheme of HDGL

Thermal treatment of steel strip

One of the most important stages in the HDGL is the thermal treatment of steel strip before zinc immersion. The annealing furnace is composed of several zones, all with the aim of submitting the steel strip to established thermal settings. Generally speaking, the steel sheet is heated to a designated temperature for a sufficient amount of time and then cooled before undergoing zinc covering (*see* Fig. 2).

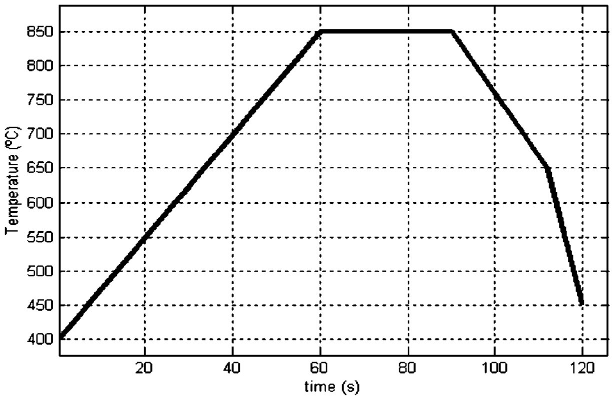
The functions in each zone in the thermal cycle are multiple:

(i) preheating and cleaning zone: first, a preheating is performed with a previous cleaning of lamination oils and other waste products, all in a low temperature (450–800°C) zone. The aim is to clean and heat the strip up to ~450°C. This temperature depends on the thickness of the strip and the thermal cycles. Also, the aim is to reduce the superficial oxide coat to a controlled thickness

(ii) heating zone: the strip temperature is increased >780°C in order to recrystallise the hard metal that comes out from cold rolling and also, to homogenise the crystalline structure. Once the target temperature is achieved, it is maintained for a period of time to ensure the growth of the grain

(iii) slow cooling zone: after this, the strip temperature is slowly cooled in a controlled way. This is performed to obtain adequate mechanical and physical properties

(iv) jet cooling zone: finally, the steel strip is subjected to a fast cooling that brings it to a more suitable temperature for the zinc coating process.



2 Thermal treatment curve

Obviously, it is very important to control the strip temperature in every stage of the process to obtain desired properties and a good coating. This control can be achieved by regulating the temperature in each area of the furnace and controlling the strip velocity between an optimal range of values.

Controlling process

Over the last few decades, different control methodologies have been developed making use of mathematical models based on differential equations. These equations help in explaining the phenomena concerning the transmission of heat by radiation and convection, even though in the last several years' research it has been more directed towards the use of neural networks to control modelling, optimisation and processes of steel manufacturing. This is due primarily to the fact that these processes and subprocesses are repetitive and highly automated and have a large number of well known variables that define them.[2,4,7,8]

Various authors have presented works in which neural networks were used in order to improve the control of the processes in the steel and iron industry in general and the process of galvanising, in particular.

Schiefer[3] *et al.* presents the control of a galvannealing process using a radial basis function network (RBFN) with online capabilities.

Schlang[8] *et al.* show diverse applications using neural networks, predicting strip temperature and the rolling force of hot rolling mills.

Lu and Markward[2] show the results of an integrated neural system, some with adaptive functions that help predict variables that are clearly significant (coating weight, line speed, etc.), therefore improving the final quality of the coating.

Kim[9] *et al.* use a principal component analysis inside the reheating furnace of a rod mill plant in order to remove the correlation effect among various measurements and to reduce the problem of dimensional control.

He also uses expert networks to develop an inverse model which predicts set points for three heating zones, using billet type at the furnace inlet and the billet target temperature at the furnace outlet.

Bloch[10] *et al.* use an RBFN to determine the optimal thermal cycle of the coating process according to the characteristics of each strip, including the speed of the strip and required thickness of the zinc coating. Once the objective temperature is determined, a diagram for controlling the process is created from an inverse model of the furnace, obtained by means of a multilayer perceptron (MLP) neural network, which is trained using robust methods.

Gorni[7] reviews the diverse uses of the neural networks applied in hot rolling processes in order to predict the final characteristics of the steel or, to determine the most appropriate settings for the process.

Pernía-Espinoza[11] *et al.* report the effectiveness of robust learning algorithms in order to predict the velocity set point in an HDGL for a coil depending on its characteristics and the furnace condition for this coil.

Basically, most authors agree that these processes can be improved using neural networks, although in practice, diverse statistical techniques and advanced types of neural networks should be combined in order to obtain systems of control that work well in all situations.

An efficient control of the heat treatment in the HDGL is fundamental for the process of coating as well as the improvement of the properties of the coil's steel and for the reduction of the costs of energy.

Owing to this, one of the objectives in the present project has been to achieve suitable temperature settings of the furnace for each coil that forms the strip, according to its physical chemical characteristics and the inertia of the line's furnace. These settings are optimised in the zone of the strip composed of only one coil, as well as in those zones of transition between two coils with different characteristics.

Presently, within the plant where these studies have been carried out, the heat control is carried out in two different ways, 'automatically' and 'manually.'

When performed automatically, the settings of the furnace are handled by an analytical model based on differential equations that are designed to predict the temperature of the final strip, using its dimensions (width and thickness), speed of the strip, the type of steel, the temperature of the steel upon entrance and the temperatures of the furnace.

Other times, especially with certain types of coils, the settings of the furnace are performed manually by an operator, based on his or her experience and the use of setting tables, pre-established empirically.

Artificial neural network (ANN)

An artificial neural network[12–14] is an electrical, mechanical or computational model of an interconnected group of artificial neurons that is inspired by the way biological nervous systems, such as the brain, process information. The large number of highly interconnected groups of artificial neurons use a mathematical or computational model for information processing based on a connectionist approach to computation.

In a typical ANN, each node operates on a principle similar to a biological neuron, in which each incoming synapse of a neuron has a weight associated with it. Each node has a set of input lines (which are analogous to input synapses in a biological neuron) and an 'activation function' (also known as a transfer function), which tells the node when to fire (similar to a biological neuron).

The ANN must be 'trained' to simulate the desired behaviour using a training algorithm with a large amount of training data. After this process, it is necessary to test the ANN with new data.

There are many types of ANN, however, the most popular one is the feed forward neural network composed of a set of nodes arranged in layers and connections. The connections are typically formed by connecting each of the nodes in a given layer to all of the neurons in the next layer.

The most popular feed forward neural network is the MLP. This class of networks consists of multiple layers of nodes interconnected in a feed forward way, with nonlinear functions, usually sigmoid functions, as activation functions and trained with back propagation training algorithm.

An MLP is generally used because it is considered a universal function approximator by the universal approximation theorem. This theorem states that every continuous function that maps intervals of real numbers to some output interval of real numbers can be closely approximated arbitrarily by an MLP with only one hidden layer. This result holds only for restricted classes of activation functions, e.g. for the sigmoidal functions.

Genetic algorithms

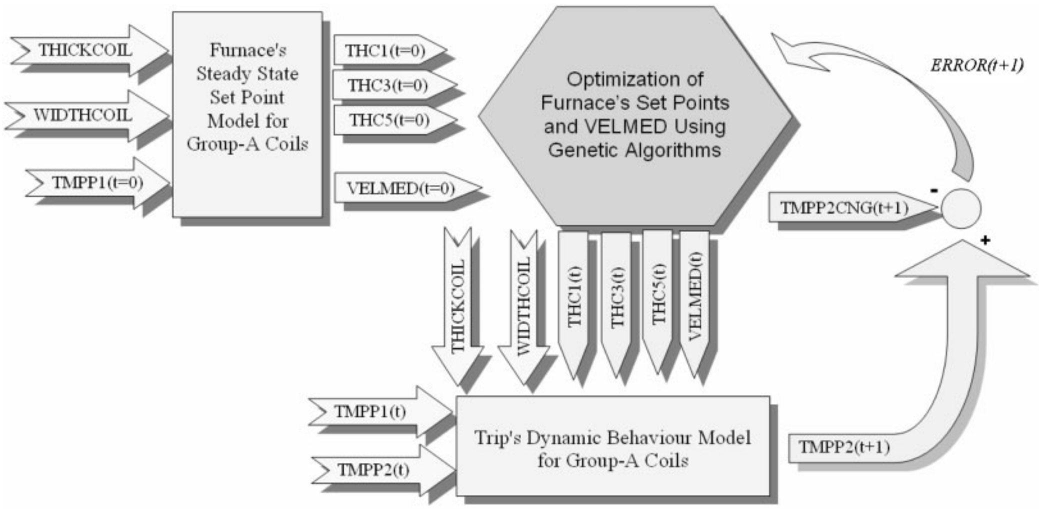
Genetic algorithms[15,16] are systematic methods used to solve search and optimisation problems and apply to such problems the principles of biological evolution, namely, selection of the 'fittest', sexual reproduction (crossover) and mutation.

Suppose that we have a mathematical model or function $f(x_1,\cdots,x_n)$ and want to find a solution $(x_1,\cdots,x_n)$ that maximises or minimises that function, or, that yields a result that approaches on of these maximums or minimums.

First, a basic genetic algorithm creates an initial generation or population of N individuals or random solutions $G_0(k)=(x_{k11,\cdots,}x_{kn})$ encoded in chromosomes and evaluated using the model $f(x_1,\cdots,x_n)$ in such a way that the best individuals will be those whose result approaches the desired maximum or minimum.

The genetic algorithm consists in a repetitive process of the creation of generations of individuals based on other individuals from previous generations until finally, the result obtained by the best individual of each generation converges with a value near the desired minimum or maximum.

Generally speaking, each generation of individuals $G_n(k)$ is created using the previous population $G_{n-1}(k)$ so that a small percentage is formed by the best individuals (in other words, by the selection of the 'fittest') and another percentage (usually high) comes from the obtaining of the chromosomes of individuals from the previous generation by crossover (sexual reproduction) and another small percentage is created using the chromosomes selected from the previous population and whose genes are randomly altered (by mutation). Such genes are part of the chromosome and



3 Application's scheme

their structure depends on the way in which each solution is encoded.

In the following section, an application based on MLP neural networks and genetic algorithms is posed[17] which simulates and plans offline the best speed and temperature settings for the zones of the furnace for each coil that forms the strip. In this way, it was sought to reduce the error between the target temperature of the strip and its actual temperature when exiting the furnace.

Methodology

Methodology[17] based on neural networks and genetic algorithms allows the best speed and temperature settings in the zone to be determined in order to reduce the margin of error between the final temperature and expected temperature.

Fundamentally, the proposed system seeks to improve the heat treatment of the strip whenever there are changes in thickness and width, or when there are different steel types present in the coils.

The methodology is based on the use of two types of models, both developed using neural networks MLP, a model that allows to establish settings of the furnace in a steady state and a model that is used to determine dynamic behaviour of the strip when faced with fluctuations in temperature of the furnace (*see* Fig. 3).

It is reasonable to say that studies have been developed for the coils of steel with a similar chemical composition. Later on, it is proposed that the RBFN be used, which makes it possible to approach the problem for different types of steel, as well as the methodologies of robust and spurious training.[11,18]

Database

Data acquisition was performed by experts from the computer processing area based on historic data continuously generated during galvanising process (initially more than 6000 variables). The variables were selected according to their relevance to the process (furnace heating zone). The database used in the present paper was composed of variables such as temperature, velocity, thickness, width and the coil code (which is a numerical designator of production sequence). Finally, each variable was defined by 30 920 data points.

All variables were measured at 100 m intervals along the strip. The strip velocity was measured in the centre of the furnace and it is reasonable to assume that the strip maintained the same velocity throughout the heating zone.

Model for furnace settings in fixed setting

Input for the model is as follows: the width of the coil (widthcoil), its thickness (thickcoil) and the temperature of the strip upon entrance (TMPP1) and as output: the temperature of the three zones of the furnace (THC1=initial zone, THC3=intermediate zone, THC5=final zone) and the speed of the strip (velmed).

This network is only trained for those cases in which the temperature of the input and output are in a steady

Table 1 Relevant variables and their abbreviations

Abbreviation	Meaning
Velmed	Strip velocity inside furnace, m min^{-1}
Thickcoil	Strip thickness at input of furnace, mm
Widthcoil	Strip width at input of furnace, mm
TMPP2	Strip temperature at output of heating zone, °C
TMPP2CNG	Strip set point temperature at output of heating zone, °C
TMPP1	Strip temperature at input of heating zone, °C
THC1	Zone 1 set point temperature (initial Heating zone), °C
THC3	Zone 3 set point temperature (intermediate heating zone), °C
THC5	Zone 5 set point temperature (final heating zone), °C

state and errors of the final temperature of the strip have been reduced (difference between the target and actual temperature of the strip at the exit of the furnace). In this way, the model 'learns' to predict the correct temperature settings of the furnace and the speed of the strip for the coils with different thickness and widths, both when the settings are controlled manually and when the system runs automatically. In other words, it 'learns' from the experience of the human operator when the process is correctly performed by hand, as well as from the mathematical model when the control is correctly carried out automatically.

Model of dynamic behaviour of strip

This model seeks to predict the behaviour in the temperature of the strip when faced with fluctuations in temperature or changes in the speed of the process.

It requires the following variables as input: temperature of the strip at the entrance of the furnace in instant t [TMPP1(t)] as its derivative, temperature of the strip at the exit of the furnace in instant t [TMPP2(t)], the thickness and width of the strip in this instant (thickcoil and widthcoil) and its derivatives, the temperatures of zones 1, 3 and 5 of the furnace in instant t [THC1(t), THC3(t) and THC5(t)] and its derivatives and the speed of the strip at instant t [velmed(t)] and its derivative. As output, the model yields: the temperature of the strip at the exit of the furnace in instant $t+1$ [TMPP2($t+1$)].

In short, the first model allows the best temperature and speed settings to be found for each type of coil, while the second model helps to know in advance the behaviour of the temperature of the strip in the face of setting variations in the furnace and the speed of the process.

Logically, these models should be created for coils whose chemical compositions of steel are similar. For that reason, a non-linear Sammon[19] projector is used (even though other types of projectors or cluster algorithms can be used) to group the coils with similar steel types together. This algorithm uses non-linear transformations to project the original space into a space with smaller dimensions, therefore preserving the inherent structure of the data. In this way, the high dimensionality can be projected on to two-dimensional graphs, maintaining the same proportions between the distances of the coils.

This type of projector has the advantage that its application is very simple and allows, as long as the final error is small, to visualise with precision the relative distances between the points on a two-dimensional map.

Next, the two networks previously described for each type of steel are created, for which it is necessary to have a large number of historical data from each group of coils.

Once the models for each group of coils with similar steel compositions are established using the predicted scheduling, the settings of the furnace and the behaviour of the strip are simulated and optimised with genetic algorithms until finally the settings which best allow reducing the error between transitions are obtained.

Stages of methodology

The methodology proceeds in the following stages:

(i) the use of a non-linear classifier to group the coils with similar mechanical and thermal characteristics

(ii) the creation, for each group of coils and from the historical data of the process in a fixed setting and with a small margin of error, of a network of temperature settings of the zone in furnace, temperatures of the strip settings and different speeds, with validation of the degree of generalisation obtained

(iii) also, the development of the model of dynamic behaviour in the face of the changes of speed and temperature is performed separately for each group of coils, with validation of the degree of generalisation of the model created

(iv) once the two models, as well as the predicted scheduling for each group of coils is obtained, the zone temperatures and speeds in the face of the changes of dimensions and/or the temperatures at entrance of the strip are simulated

(v) by means of genetic algorithms or other optimisation techniques, the best setting to reduce the error in the transition of the coils is sought

(vi) the optimum setting points are stored for the moment in which they will be used to carry out the process.

Experimental results and discussion

Use of Sammon projector

Initially, a table of 2436 coils was made, comprised of code of the coil, code of the continuous casting and 14 indicators concerning chemical composition of the coil's steel.

Aside from the 14 elements reported for chemical composition of all steel coils, the non-linear Sammon[14] projector was used to determine how they were arranged and mapped within the space $\Re^2$ with an objective error of 0·001.

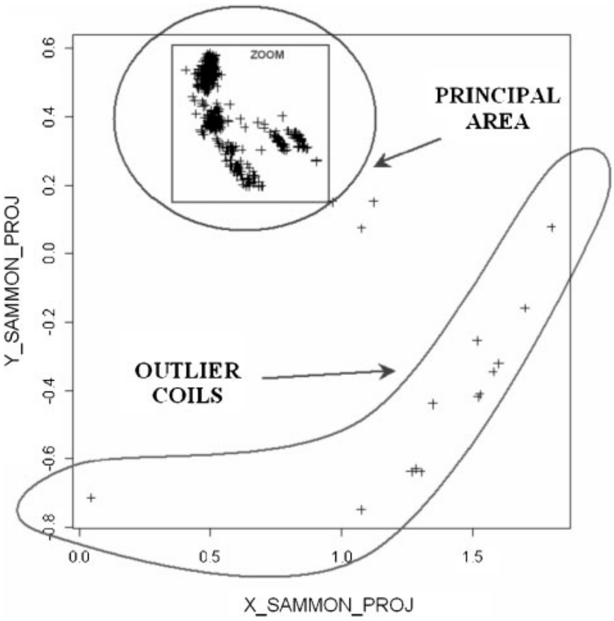
Before carrying out the projection, the components were standardised and assigned weighted coefficients depending on the degree of influence that each one had within the heating process. These coefficients were applied empirically using expert knowledge from the industrial plant. From this process, it was clear that only some of the components were responsible for influencing the classification process described above.

In Fig. 4 it can be seen that several series of outlier coils clearly appear to be separated from the majority of the zone of interest. The majority of the coils that fall in the upper left corner form two principal groups and two or three secondary groups (*see* Fig. 5).

From analysis of these graphs, the following conclusions were drawn:

(i) two principal and three secondary groups of coils existed according to the chemical composition of their steel

(ii) there were coils whose steel was completely distinct from the rest and that probably had different mechanical and thermal properties as well. It was found that the use of this projector was able to help locate, within a prepared sequence, those coils whose steel types were different from the rest and, therefore, capable of causing problems in the galvanising process. Using the coordinates of the projected points, the problem coils were located before the



4 Sammon projection of coils according to chemical composition and enlargement of projection around main distribution

treatment was performed and separated from the scheduling.

Creation of settings model

In this phase, the object was to find, in the 'manual mode' as well as the 'automatic mode'. Those cases, in a steady state, had produced a low margin of error. In this way, a non-linear neural network was created to predict the variables of the optimum settings for each coil according to its width, thickness upon entrance and temperature upon entrance.

For that reason, an MLP with 17 neurons in the hidden layer and optimised topology was trained.

The training method was that of cross validation; 80% of the data for the training and the other 20% of the data from tests not used in the creation of the neural network to verify the degree to which the network was generalised.

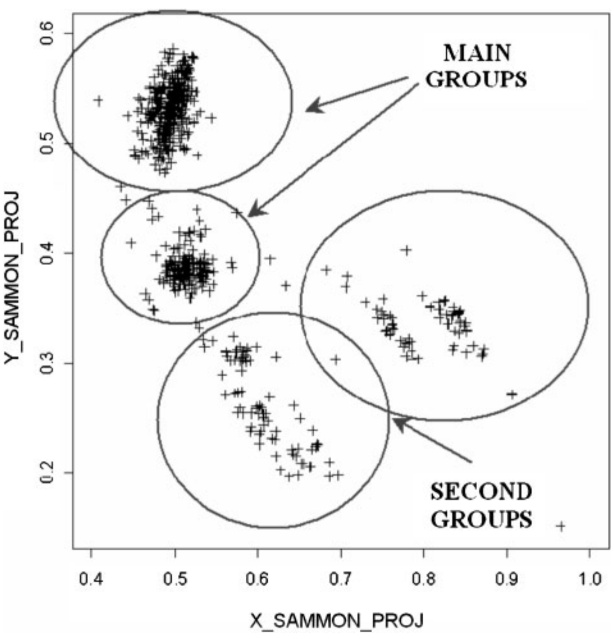
After multiple trainings, the best network with the following results was selected:

(i) MSE error from training: 0·00070; a 2·64% margin of error from training
(ii) MSE error from testing: 0·00075; a 2·74% margin of error from testing with unused data in the training.

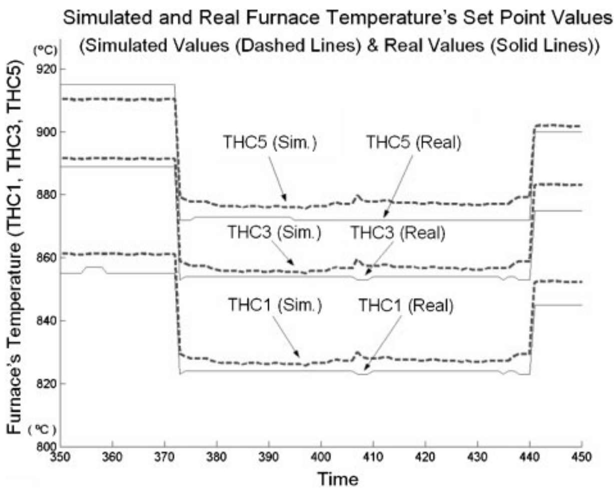
In Fig. 6 it can be seen how the obtained model predicts with considerable precision the temperature settings of the three zones in the furnace [THC1 (Sim.), THC3 (Sim.) and THC5 (Sim.)] with respect to the actual temperature settings that were used.

Similarly, in Fig. 7, it is clear that the model is capable of simulating with great precision the velocity of the strip [velmed (Sim.)] with respect to the actual velocity that was used.

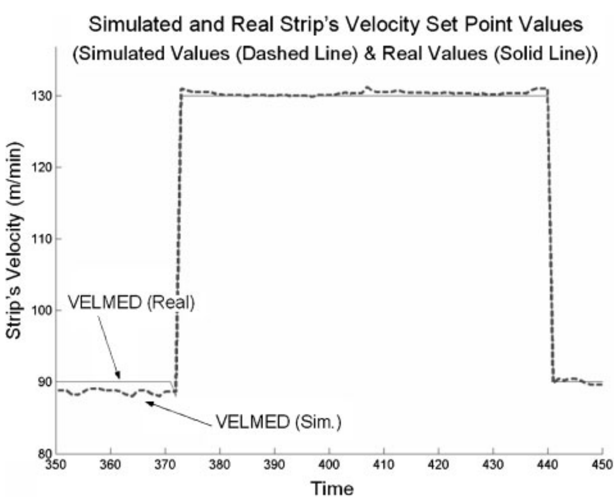
Both figures correspond to data that was not used in the training process of the model, such that it is demonstrated that the degree of generalisation of the data is very acceptable.



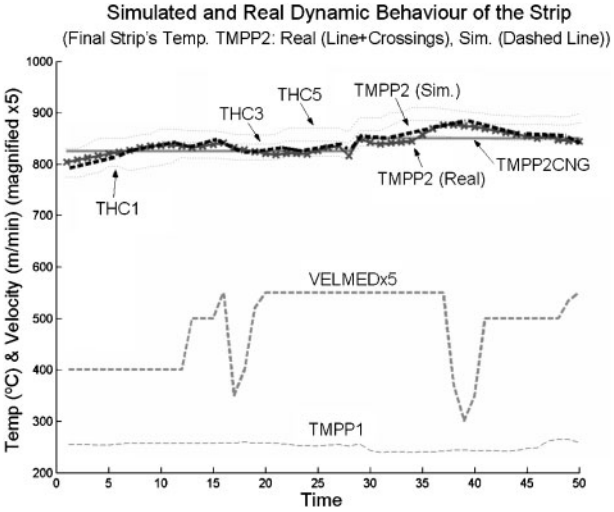
5 Principal groups of coils in Sammon projection



6 Comparison with new database of real data and data which model predicts: solid line – real temperature settings of furnace zones; broken line – simulated temperature settings of furnace zones



7 Comparison with new database with data of speed settings (solid line) [velmed (real)] and strip's velocity [velmed (Sim.)] that model predicts (broken line)



8 Comparison with new database of TMPP2 (real) (solid black line) in front of strip temperature at output of furnace that predicts neural network TMPP2 (Sim.) (black dotted line)

Creation of non-linear model of dynamic behaviour of strip

Once a non-linear model was obtained that allowed determining the temperatures of the furnace settings and the speeds of the strip settings according to the thickness, width and temperature of the strip upon entrance, a model was developed to explain the dynamic behaviour of the strip with respect to the variations of furnace temperature and speed of the strip.

Different types of neural networks were trained (with the same methodology described above) with the input corresponding to the variables: settings of the furnace, speed of the strip, temperature of the strip upon entering and exiting the furnace, dimensions of the strip and all of the derivatives of the mentioned variables.

Because the amount of input was excessive (15 inputs) and highly dependent, the dimensions were reduced to nine independent variables using the principal component analysis.

The results obtained from the training and testing of the best network are as follows:

(i) training of MSE: 0·0019 (4·36% margin of error)
(ii) testing of MSE: 0·0033 (5·74% margin of error).

Figure 8 shows the final temperature predicted by the model TMPP2 (Sim.) closely approaches the final temperature that was produced in the steel strip TMMP2 (real). In this case, TMMP2 (Sim.) is obtained using the temperatures of the furnace (THC1, THC3 and THC5), the average velocity of the strip (velmed), the strip temperature upon entrance into the furnace (TMPP1), the expected temperature of the strip (TMPP2CNG) and the physical characteristics of each coil.

The results were checked with a different database and the error was not observed to >10°C.

Optimisation by means of genetic algorithms

Once the neural networks for each group of coils were derived, the behaviour of the strip relative to different temperature settings in the furnace and the speed of the strip were simulated with the intent to reduce the errors produced when there were changes in thickness, width and types of steel among welded coils that formed the strip.

In this manner, it was attempted to reduce the average error in the temperature of the actual and real settings, looking for straight lines to smooth out the transitions of the following settings: the temperatures of the three zones of the furnace and the speed of the strip. The settings were optimised using genetic algorithms that modified variables position and width of the straight lines of adjustment for each of the settings (*see* Fig. 9).

In Fig. 9 it can be observed the straight line adjustments (SLA) of the furnace temperatures SLA THC1, 3 and 5 and the speed of the strip SLA velmed from a transition between coils with different widths (1200 and 1150 mm) where the greatest error between the real temperature of the strip TMPP2 (real) and the expected temperature TMPP2CNG was 50°C.

The objective consisted in optimising the position and width of the SLA's so that the final temperature of the strip TMPP2 (Sim.) was as close as possible to the target temperature TMPP2CNG.

Using genetic algorithms, it was attempted to obtain new straight lines of adjustment in settings to reduce the final, average expected error of the strip. In other words, it was sought to minimise the maximum value of difference between the temperature settings of the strips and the actual temperatures for each transition between coils.

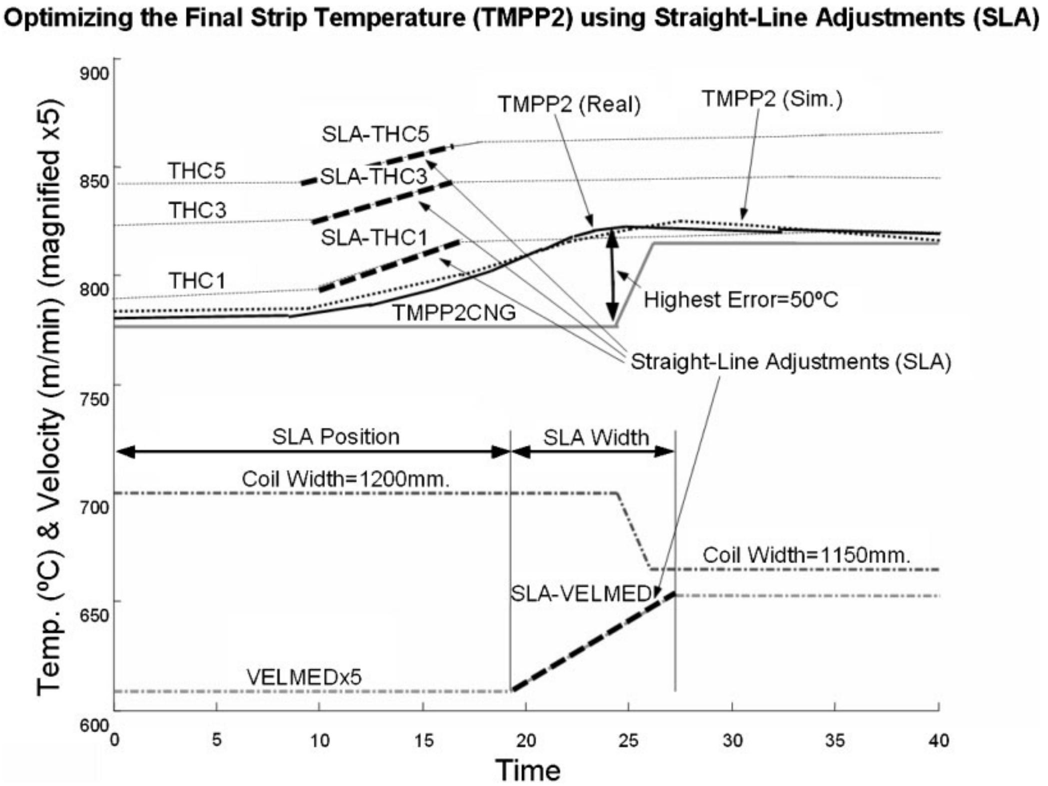
The algorithm was based on the following algorithm:

(i) create 1000 chromosomes with random values for variables (first population) of position and length of the straight line adjustment of the temperature settings of zone 1, 2, 3 and 5 in the furnace and of the strip
(ii) using the settings of each chromosome, simulate the behaviour of the strip and obtain the maximum error instantaneously between the obtained temperature of the band and the actual temperature
(iii) obtain the top 20% best chromosomes (with the least error)
(iv) create 70% new chromosomes with the crossover of the 20% best
(v) create another 10% with mutations
(vi) create a new generation of 1000 chromosomes from those obtained in steps 3, 4 and 5
(vii) repeat steps 2 and 6, saving the results from each generation.

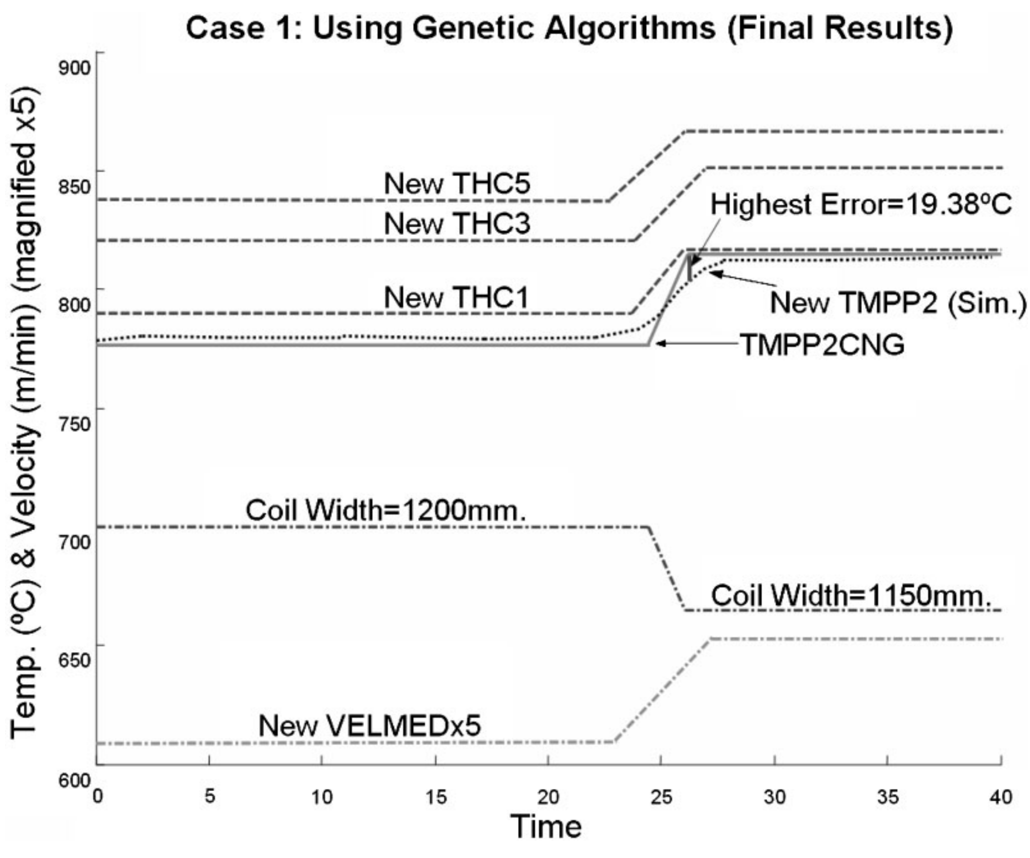
After the seven generations of individuals, the average error of the temperature ended up at 7·31°C, contrasted with 15·1°C of average error in the beginning and a value of 19·38°C of maximum difference, as opposed to a maximum of 50°C initially (*see* Fig. 10).

In Fig. 10, it is clearly demonstrated that the SLA changed the position and width such that new temperature (new THCx) and velocity (new velmed) settings were found which considerably reduced the expected error between the strip temperature [new TMPP2 (Sim.)] and the target temperature (TMPP2CNG).

By using this method, it is possible not only to determine the best furnace setting for each of the coils according to their thickness, width, temperature upon entering the furnace and type of steel, but also to optimise these settings in the transition between coils, therefore considerably improving the heat treatment.



9 Straight lines of adjustments for transitional setting of two consecutive coils



10 Optimisation using genetic algorithms

This improvement indicates that a more precise fit related to both the desired temperature of the strip and its homogenisation was obtained.

Conclusions

The present article presents a methodology based on neural networks and genetic algorithms that can help considerably in predicting the best settings for controlling the annealing process of an HDGL and consequently, to increase the quality of the final product. These can easily be applied to the diverse systems of control previously mentioned, being used as setting signals or as variables of validation for other models.

It has been shown that the generation of setting models that 'learn' from the experts of the plant, or from the actual software and control and from other models that account for the dynamic behaviour of the strip can be extremely helpful in simulating the system and in finding the settings which best reduce the error in transitions of the coils. This search can be performed with genetic algorithms or with other optimised techniques.

Furthermore, the methodology presented here is easily adapted to virtually any industrial process in which it has a sufficient volume of historical data at its disposal.

From the results hereby obtained, the development of new methods of control that are more efficient and, that make use of adaptive robust neural networks from the RBFN and other, quicker methods of optimisation is proposed.

Acknowledgements

The present work has been supported by the Spanish Ministry of Science and Technology (MCYT) by means of the Research General Direction (Dirección General de Investigación) project: DPI2004-07264-C02-01. The authors also want to recognise the support received from the '2° Plan Riojano de I+D+I' of the Government of La Rioja. It also has been partially funded by the European Union under the RFCS programme references RFS-CR-03012, RFS-CR-04023 and RFS-CR-04043 and the Ceutic Interreg IIIA programme.

Finally, the authors would like to thank the company Aceralia (Arcelor group), the Division of Computer Processing and the Division of Innovation and Research, for all of the support and information provided for the writing of the present article.

References

1. J. A. González-Rodríguez: 'Predicción de la Calidad de Bandas Laminadas en Caliente Mediante Modelos Inteligentes', PhD thesis, Universidad de Oviedo, Mieres, Spain, 1994.
2. Y. Lu and S. W. Markward: *IEEE Trans. Neural Network.*, 1997, **6**, (8), 1328–1337.
3. C. Schiefer, H. P. Jörgl, F. X. Rubenzucker and H. Aberl: Proc. 14th IFAC World Cong., Vol. Q, 61–66; 1999, Beijing, China.
4. J. Tenner, D. A. Linkens, P. F. Morris and T. J. Bailey: *Ironmaking Steelmaking*, 2001, **28**, (1), 15–22.
5. N. L. Samways: *Iron Steel Eng.*, 1993, **70**, 56–62.
6. W. Vermeulen, A. Bodin and S. Van der Zwaag: *Steel Res.*, 1997, **68**, (1), 20–26.
7. A. A. Gorni: 'The modelling of hot rolling processes using neural networks: a bibliographical review', 1998, available at: www.gorni.eng.br/e/neural_1998.html.
8. M. Schlang, B. Lang, T. Poppe, T. Runkler and K. Weinzierl: *Contr. Eng. Pract.*, 2001, **9**, 975–986.
9. Y. I. Kim, K. Cheol Moon, B. Sam Kang, C. Han and K. Soo Chang: *Contr. Eng. Pract.*, 1998, **6**, 1009–1014.
10. G. Bloch, F. Sirou, V. Eustache and P. Fatrez: *IEEE Trans. Neural Network.*, 1997, **8**, (4), 910–918.
11. A. V. Pernía-Espinoza, J. B. Ordieres-Meré, F. J. Martínez-de-Pisón and A. González-Marcos: *Neural Networks*, 2005, **18**, 191–204.
12. R.O. Duda, P. E. Hart and D. G. Stork: 'Pattern classification', 2nd edn; 2001, New York, Wiley.
13. S. Haykin: 'Neural networks: a comprehensive foundation'; 1999, New York, Prentice Hall.
14. C. M. Bishop: 'Neural networks for pattern recognition'; 1995, Oxford, Oxford University Press.
15. M. Mitchell: 'An introduction to genetic algorithms'; 1996, Cambridge, MIT Press.
16. D. E. Goldberg: 'Genetic algorithms in search, optimization and machine learning'; 1989, Boston, MA, Kluwer Academic Publishers.
17. F. J. Martínez-de-Pisón: 'Optimización mediante técnicas de minería de datos del ciclo de recocido de una línea de galvanizado', PhD thesis, Universidad de La Rioja, La Rioja, Spain, 2003.
18. A. V. Pernía-Espinoza, M. Castejón-Limas, A. González-Marcos and Vanesa Lobato-Rubio: *Ironmaking Steelmaking*, 2005, **32**, (5), 418–426.
19. J. W. Sammon: *IEEE Trans. Comput.*, 1969, **5**, 401–409.