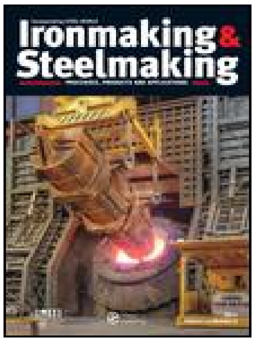

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Estimation of mechanical properties of steel strip in hot dip galvanising lines

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In this paper, the application of data mining and artificial intelligence techniques stemming from other problem areas to the particular case of a galvanised steel manufacturing process, is presented. The main goal is to optimise the quality control of galvanised steel by developing a predictive model of the mechanical properties according to the chemical composition and manufacturing conditions in the annealing furnace.

Keywords: Hot dip galvanising line (HDGL), Annealing, Data mining, Artificial intelligence I&S/1816

Introduction

Galvanised products have a long life and excellent corrosion resistance. Zinc provides twofold protection for the steel base, adding the galvanic action specific to this element to the physical barrier of the coating itself. Thus, the use of galvanised products is increasingly popular for a large number of applications. These applications can be used both indoors in hidden areas and outdoors in exposed areas. Construction, agriculture and domestic appliances are some of the most common applications. The use of galvanised products in the automotive industry has increased over the years as a response to the ever increasing requirements for improved corrosion resistance, paint adherence, surface finish, weldability and drawability.

In order to economically produce galvanised steel of excellent quality, it is necessary to control the process conditions to fulfil all quality demands. There have been improvements in the modelling and control of the annealing furnace[1,2] and in the coating system control,[3–5] as well as in other areas. The present paper describes the control of the mechanical properties, and therefore, the drawability, of galvanised steel using data mining and artificial intelligence techniques.

First, a description of the continuous galvanising process and control system of mechanical properties currently used at the most important steelmaking company in Spain is given. Then, the different techniques used to develop the model are described. Finally, the results are depicted to demonstrate the performance improvement of the control system and its main advantages.

Continuous galvanising steel line

The analysed continuous galvanising line produces galvanised sheets and coils using various grades of cold rolled steel strip base suited to the final use of the product required. First, in order to form a continuous strip, coils are uncoiled and a shear cuts off the end of each coil so that they can be welded together. Then, the oil, dirt and oxides on the surface of the cold rolled coils are removed before the strip enters the annealing section of the line. A good adherence, necessary to obtain an excellent coating quality, is achieved by perfect strip cleaning.

The clean strip passes through the annealing furnace to give steel the desired properties by heating it to particular temperatures and profiles that determine the grain structure within the metal and prepare it for the galvanising process. The entire process is carried out in a protective atmosphere that also reduces the surface of the strip used in the coating preparation step. The annealing cycle has the following phases (Fig. 1):

(i) the cold strip is recrystallised by heating it to the highest temperature of the annealing profile
(ii) the strip temperature is maintained and grain growth takes place
(iii) an initial slow cooling period is used to control the metal texture
(iv) then, a fast cooling period prepares the steel for the strain aging treatment. The strip is cooled to a temperature appropriate for the coating step
(v) the overaging step results in the precipitation of carbon to an extent that reduces the solute carbon. Thus, the strain aging tendency of the strip is reduced.

After the annealing step, the strip enters the molten zinc bath in order to form a zinc coating that is metallurgically bonded to the steel surface. The coating thickness is controlled by air knives installed after the zinc bath. The control of the coating thickness is one of the most critical areas of development for coated sheets.

Finally, the coated strip is subjected to a chromate conversion treatment by the application of chromate solutions to the strip surface. This chromate treatment results in a surface resistant to corrosion during storage and transport until the steel can be used in other applications.

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1 Example of annealing profile

Control system for mechanical properties

Nowadays, the mechanical properties of galvanised sheets and coils are measured after their fabrication. Owing to the offline control, a large dead time occurs which makes the control solution inefficient. That is, the continuous galvanising line produces at least two coils or sheets from the very moment a coil with undesired properties is detected until appropriate actions are taken. Such a delay results in the cost for each coil of an inappropriate quality.

In order to improve the control system and allow for online control of the desired mechanical properties, data mining and artificial intelligence techniques are used to develop a predictive model. With this model, the impact of the manufacturing conditions in the annealing furnace on the final mechanical properties was analysed.

Modelling of mechanical properties

Database

The aim of the data mining analysis was to predict the yield strength, tensile strength and elongation as functions of a large number of variables, including the chemical composition, heat treatment and strip speed in the annealing furnace. Missing values could be tolerated since they made the predictions more noisy. Therefore, the database used in the present work consisted of 1731 samples. Skin pass elongation was kept out of the analysis as far as it was the same for all coils and so differences were meaningless.

Table 1 shows the range, mean and standard deviation of each variable, including the outputs (yield strength, tensile strength and elongation). The purpose here was simply to list the variables and give an idea of the range covered.

Exploratory data analysis

As a previous step to the modelling, it is often useful to visualise the experimental data in order to observe their structure, possible outliers, different groups, etc. The two main techniques used in the present work were scatterplot matrix and projection.

Scatterplot matrix

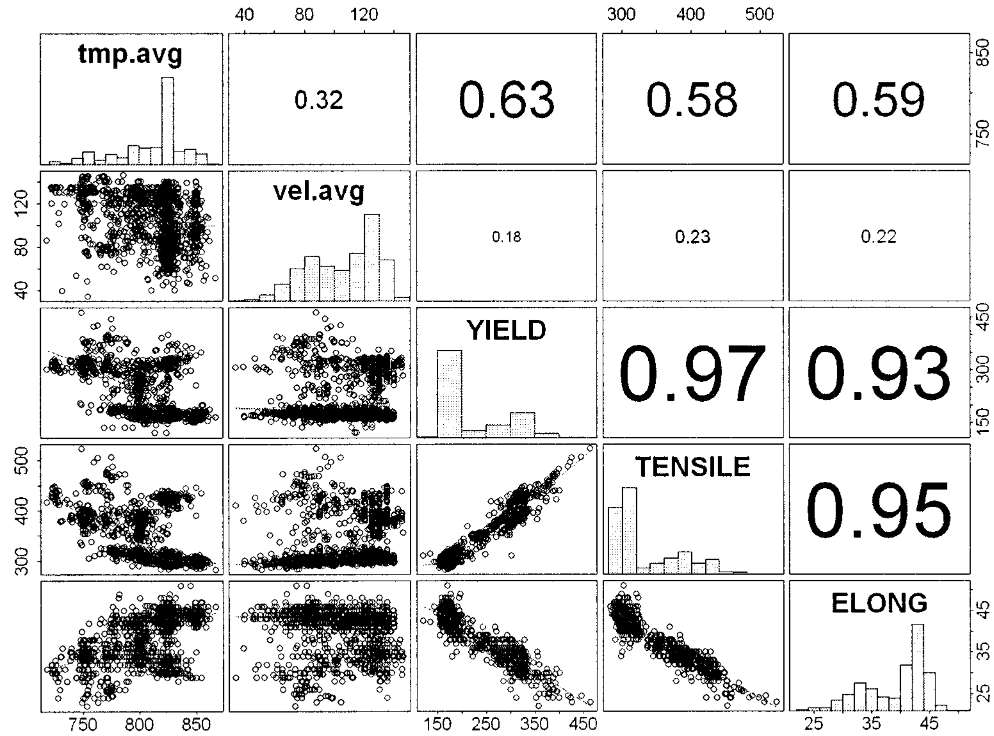
A visual inspection of all possible pairwise scatterplots in the variables gave an idea of the relationships among all variables. Figure 2 shows that there is a relationship between the strip temperature and speed in the annealing furnace and the mechanical properties analysed. This relationship was the main interest of the present work because these were the variables that could be controlled and modified during the annealing process. The impact of the chemical composition on the yield strength, tensile strength and elongation is currently the subject of further study.[6–8]

Projection techniques

Visualising the data in a seventeen-dimensional space, corresponding to the 17 input variables used in this work, is difficult. To overcome this problem, the original data was compressed by using projection techniques which project m-dimensional data onto a d-dimensional space (usually $d=2$ since the resultant data configuration can easily be evaluated manually), preserving as far as possible the original data structure. The resulting visualisation depicts clusters in input space as groups of data points mapped close to each other in the output adimensional plane. Thus, the inherent structure of the

Table 1 Variables used in developing model of mechanical properties

Variable	Minimum	Maximum	Mean	Standard deviation
Input variables				
Strip temperature at heating phase output (avg. temp.), °C	718·1	867·4	811·2	29·2188
Strip speed in furnace (avg. vel.), m min^{-1}	34	146	107·11	23·1882
Carbon, wt-%	0	0·0993	0·01399	0·0217
Manganese, wt-%	0·0859	0·5837	0·2101	0·122475
Silicon, wt-%	0·0029	0·1888	0·02265	0·046606
Sulphur, wt-%	0	0·0348	0·008517	0·002721
Phosphorus, wt-%	0·0034	0·0828	0·01711	0·017249
Aluminium, wt-%	0·0175	0·0959	0·03115	0·007588
Copper, wt-%	0·0067	0·0677	0·01525	0·006415
Nickel, wt-%	0·0125	0·0725	0·01833	0·005514
Chromium, wt-%	0·0097	0·041	0·01837	0·003867
Niobium, wt-%	0·0001	0·0547	0·002495	0·007823
Vanadium, wt-%	0·0001	0·0045	0·001875	0·001187
Titanium, wt-%	0·0001	0·0979	0·05446	0·031186
Boron, wt-%	0	0·004	0·0003006	0·000562
Nitrogen, wt-%	0·002	0·0114	0·003678	0·001053
Carbon equivalent C_{eq}, wt-%	0	0·1722	0·04943	0·035989
Output variables				
Yield strength, MPa	121·5	464	219·7	67·1917
Tensile Strength, MPa	282	523	335·1	48·6782
Elongation, %	22	51	39·79	5·3764



2 Relationship between manufacturing conditions in annealing furnace and mechanical properties

input signals can be gained from the structure detected in the two-dimensional visualisation.

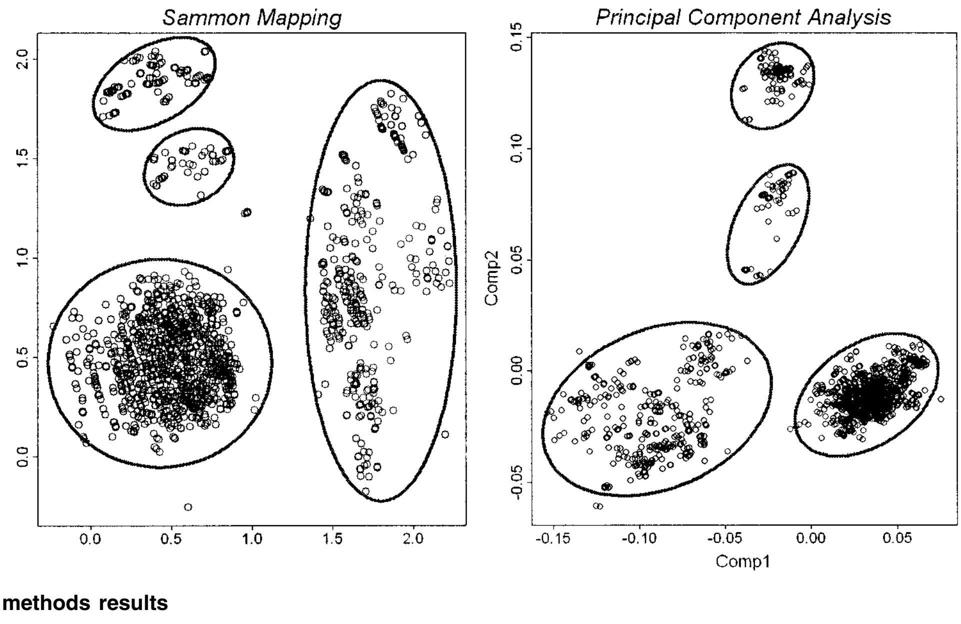
These techniques can be divided into two main groups, namely, linear and non-linear techniques. The most common non-linear technique is Sammon mapping,[9] whereas principal component analysis (PCA)[10] is the most popular linear projection.

Sammon mapping is an iterative method that uses a gradient descent algorithm to minimise the error function E, which represents how well the present configuration of the data in the d-dimensional space fits the original data in the m-dimensional space

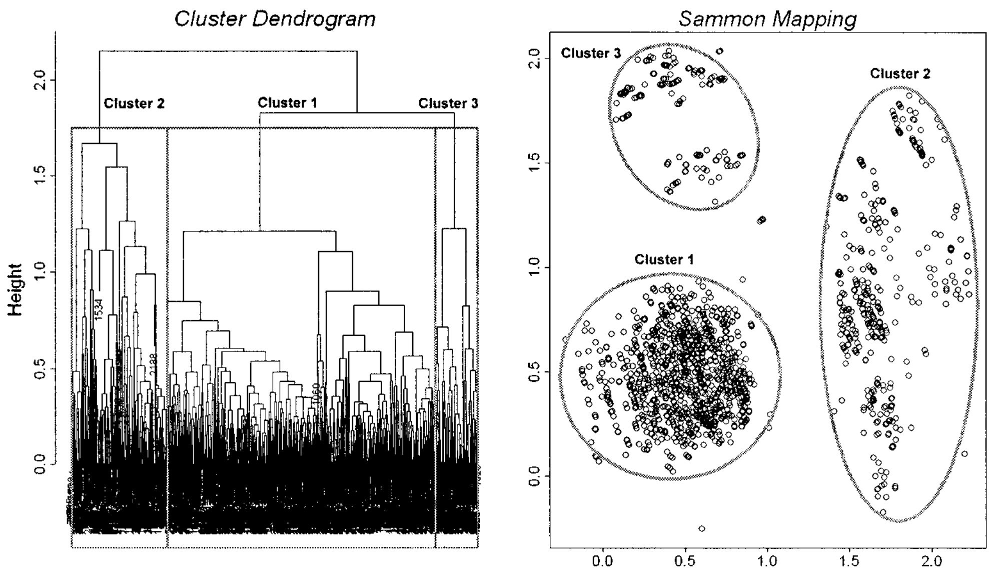
$$E=\frac{1}{\sum\limits_{i<j}\delta_{ij}}\sum_{i<j}^{N}\frac{(\delta_{ij}-d_{ij})^2}{\delta_{ij}}$$

where d_{ij} and δ_{ij} are the distances between the ith and jth vector, respectively, in the m-dimensional embedding space and in the d-dimensional projection space. Sammon mapping attempts to minimise this error by positioning the points in the lower dimensional space so that the distance between the points is as close as possible to the distance between the corresponding points in the higher dimensional space.

The principal component analysis transforms a set of correlated variables into a number of uncorrelated variables, called principal components, which are ordered by reducing variability. The uncorrelated variables are linear combinations of the original variables. It can also be seen as a rotation of the existing axes to new positions in the space defined by the original variables. In this new rotation, there will be no correlation between the new



3 Projection methods results



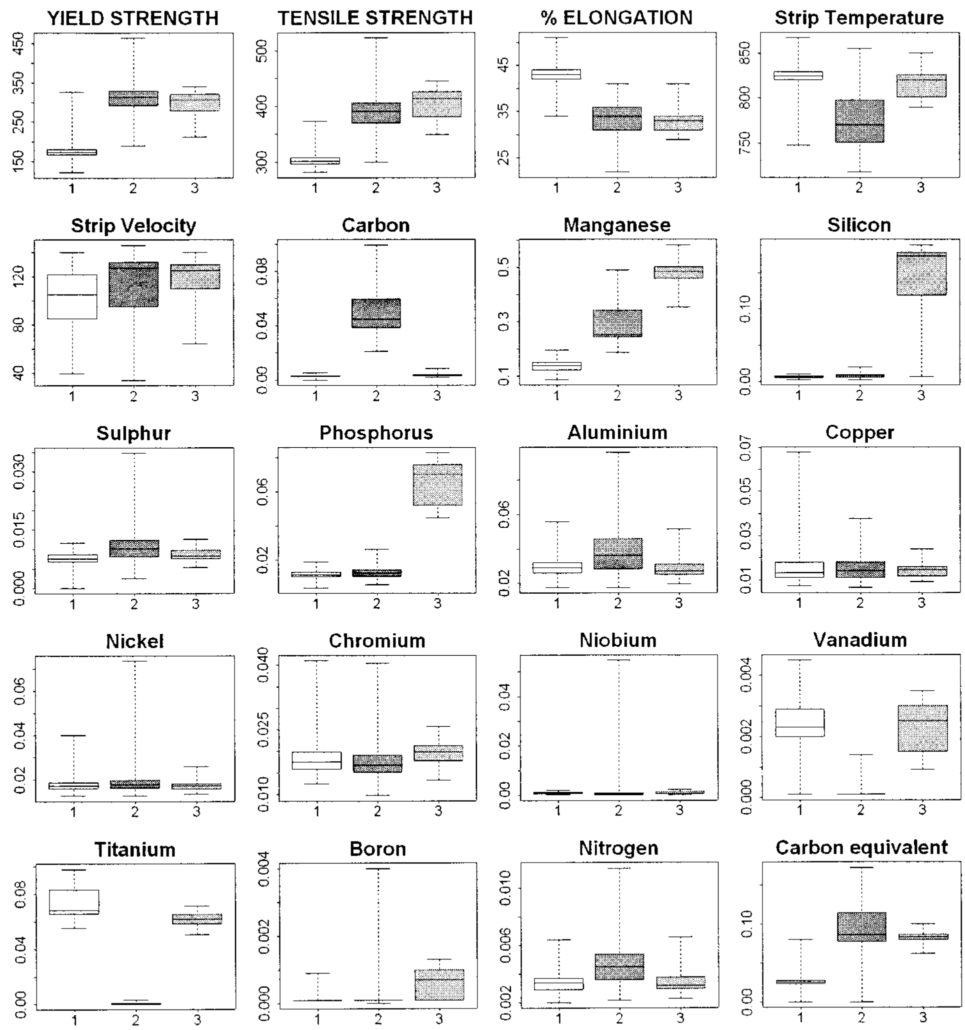
4 Results from declassification process

variables defined by the rotation. The first new variable contains the maximum amount of variation; the second new variable contains the maximum amount of variation unexplained by the first and orthogonal to the first, etc.

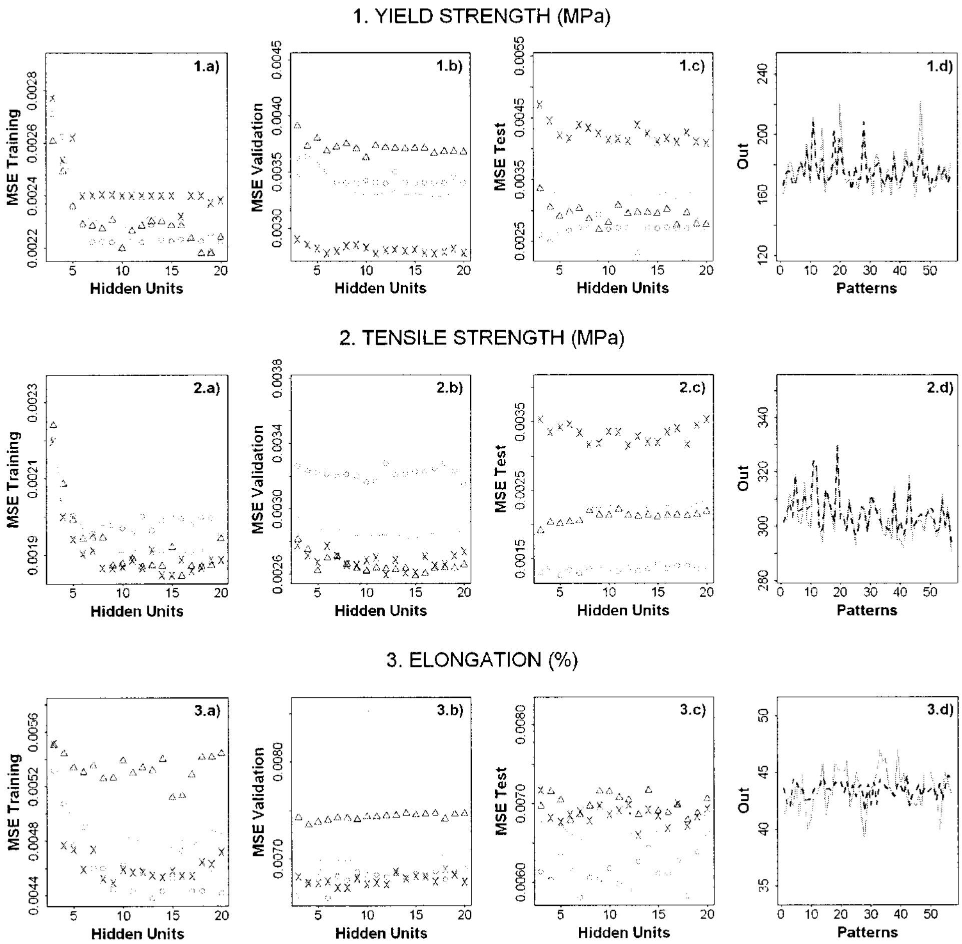
Sammon mapping in Fig. 3 reveals the existence of three or four different clusters. The results obtained using PCA were the same. Therefore, it was necessary to obtain a different model for each group.

Classification

To divide the data set into a number of disjoint classes so as to ensure that coils in the same class were similar to



5 Clustering results summary



a **training errors *v.* hidden units; *b* validation errors *v.* hidden units; *c* test errors *v.* hidden units; *d* measured output (solid line) and predicted output (dashed line)**

6 Neural network results for each model of cluster 1

one another, a hierarchical agglomerative clustering algorithm was used. Figure 4 shows the tree produced by the clustering process that divides the data into three clusters without doubt. These groups are the same as those observed in the projection techniques.

Table 2 gives the number of elements for each cluster and the differences between classes can be observed in Fig. 5: boxplots are a way of summarising a distribution. In comparing the boxplots across groups, a simple summary is to say that the box area for one group is higher or lower than that for another group. To the extent that the boxes do not overlap, the groups are quite different from one another.

Proposed models

Each model consisted of the 17 input variables and three output variables listed in Table 1. First, linear regression analysis was used to obtain the model of the mechanical properties for each cluster, but the results were not good. Then, a much more general form of regression, i.e. neural network analysis, was applied to estimate the yield strength, tensile strength and elongation of the galvanised steel.

Table 2 Number of samples for each cluster

Cluster	Number of coils
1	1142
2	407
3	182

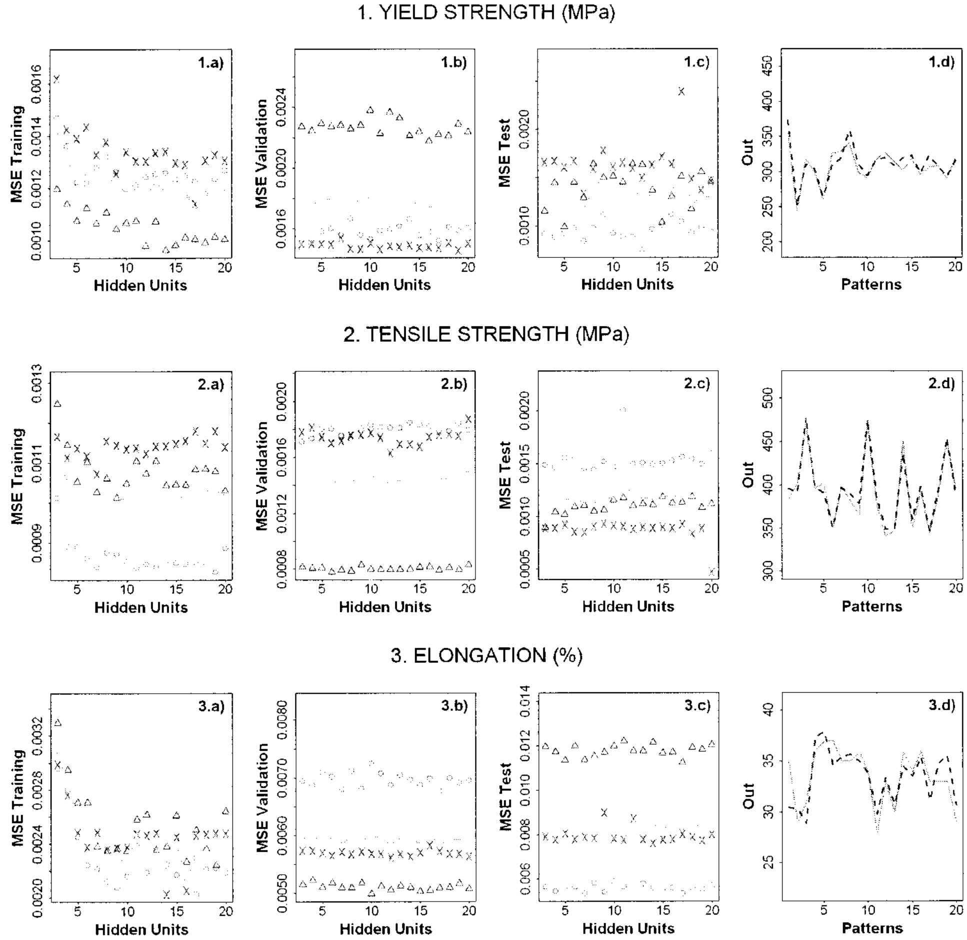
To obtain the best generalisation, the data set was randomly split into three parts:

(i) a training set used to train the neural net
(ii) a validation set used to determine the performance of the neural network on unseen patterns during learning. The learning is stopped at the minimum of the validation set error
(iii) a test set was finally used to check the general performance of the neural net.

Table 3 shows the number of randomly selected samples used in the different phases of the neural networks learning. A larger data set would be of value in creating a model based on a greater span of knowledge. However, owing to the 'small' number of patterns and in order to reduce the number of connections, a model was trained for each output instead of training a model with all of the mechanical properties.

Table 3 Split data set used in neural network learning

Cluster	1	2	3
Training set (63·3%)	723	258	115
Validation set (31·6%)	362	129	58
Test set (5%)	57	20	9
Total	1142	407	182



a training errors *v.* hidden units; *b* validation errors *v.* hidden units; *c* test errors *v.* hidden units; *d* measured output (solid line) and predicted output (dashed line)

7 Neural network results for each model of cluster 2

The data set of cluster 3 was not large enough to train a neural network with 17 inputs and 1 output, because the number of connections was high even though the hidden layer had few units. Thus, this cluster was not modelled.

The search for the predictive models was carried out by feedforward backpropagation networks with a variable number of hidden units:

(i) learning function: backpropagation with weight decay (learning parameter: 0·2; weight decay term: 0·0000005)
(ii) update function: topological order
(iii) initialisation function: randomise weights (interval: [−0·3, 0·3])
(iv) activation function: $f_{act}(x)=1/(1+e^{-x})$
(v) number of training cycles: 100 000
(vi) validation interval: 30.

To deal with the overfitting problems that occur when there are not enough examples compared to the number of input variables in supervised learning, a regularisation method called weight decay was implemented in the learning process. The application of regularisation reduces the complexity of the network and makes the learning process easier. Moreover, with the same number of training samples, a reduction in weight improves the generalisation ability of neural networks.[11]

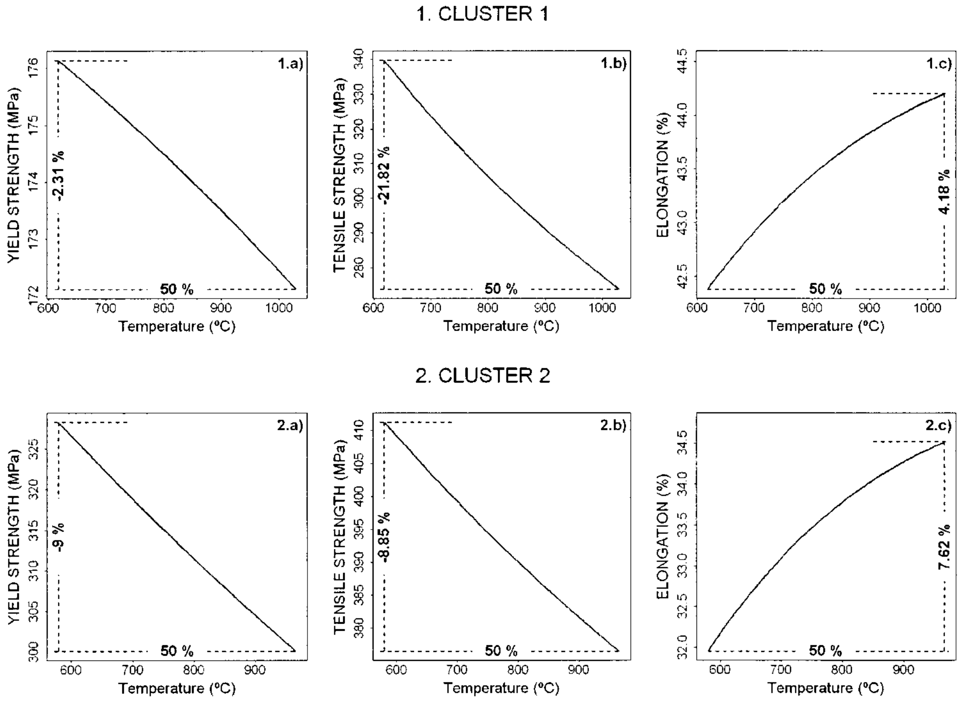
The training, validation and test errors associated with each model created, as well as the mean errors, are shown in Figs. 6 (cluster 1) and 7 (cluster 2). As expected, the training error decreased as the model became more complex, i.e. the number of hidden units increased. This was not the case for the test error. The behaviour of the best models, whose test errors were the lowest (*see* Tables 4 and 5), is illustrated in Figs. 6 and 7 as well. Note that tensile strength models had the lowest mean error (%) for each cluster and, therefore, gave the best prediction.

Quantitative impact of strip temperature and speed in annealing furnace on mechanical properties

The models developed are useful to predict the mechanical properties at the moment of the galvanised steel

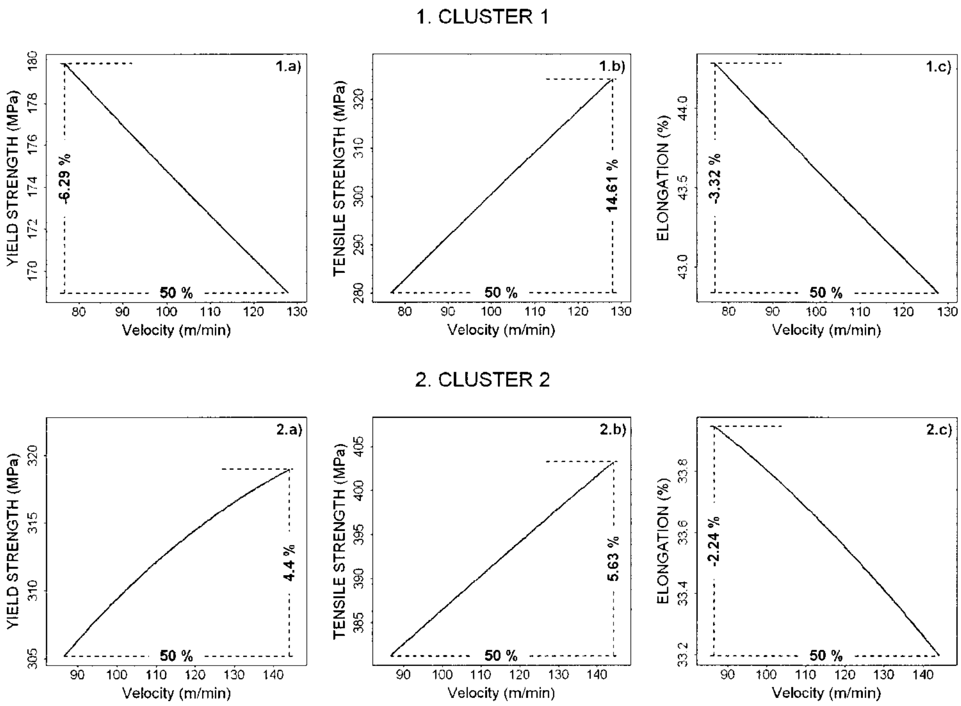
Table 4 Number of hidden units and statistics of test residuals for each model of cluster 1

Model	Hidden units	Minimum error	Maximum error	Mean error	Standard deviation	Mean error, %
Yield strength	17	−20·43	31·01	0·611	8·35	3·19
Tensile strength	12	−8·68	4·75	−0·93	9·75	0·88
Elongation	18	−4·06	2·95	−0·0122	1·63	3·07



a yield strength; *b* tensile strength; *c* elongation

8 Predicted mechanical properties as function of strip temperature



a yield strength; *b* tensile strength; *c* elongation

9 Predicted mechanical properties as function of strip speed in annealing furnace

Table 5 Number of hidden units and statistics of test residuals for each model of cluster 2

Model	Hidden units	Minimum error	Maximum error	Mean error	Standard deviation	Mean error, %
Yield strength	7	−17·9	16·36	−3·003	9·75	2·6
Tensile strength	3	−14·09	14·12	−2·74	8·05	1·82
Elongation	7	−2·53	4·57	0·052	1·78	4·3

fabrication. However, it is important to quantify the impact of the process parameters on these properties too. The knowledge of how the strip temperature and speed in the annealing furnace affect the final properties would enable more efficient control of annealing process.

The trained neural networks obtained were used to assess the impact of the process parameters for each cluster. The change in the yield strength, tensile strength and elongation with the manufacturing conditions in the annealing furnace could be quantified by selecting multiple test data sets, creating new ones by increasing and decreasing the temperature and speed variables, and analysing the estimated outputs.

Figure 8 shows that the yield and tensile strength decreased when the strip temperature increased. Therefore, it is not surprising that elongation increased with temperature. Note also that the impact of temperature was more pronounced for the tensile strength model of cluster 1.

The sensitivity to strip speed is shown in Fig. 9. Tensile strength was directly proportional and elongation was inversely proportional to strip speed in both cluster 1 and cluster 2. However, yield strength decreased in cluster 1 and increased in cluster 2 when the speed increased.

Conclusions

It has been shown that it is possible to create reasonable neural network models for the mechanical properties analysed considering the chemical composition and manufacturing conditions in the annealing furnace. The proposed models represent an advance in the hot dip galvanising process as the prediction of the mechanical properties of steel strips with this online method allows optimisation of the quality control system. The decrease in the number of destructive measurements, on the one hand, and the increase in the quality of the product by eliminating dead time in the control system, on the other, lead to production costs savings. Furthermore, it is possible to produce a more detailed feature sheet for the manufactured galvanised steel as the furnace variables are measured each 100 m.

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