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Property Prediction of Continuous Annealed Steels

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ABSTRACT

To compete in the current economic climate steel companies are striving to reduce costs and tighten process windows. It was with this in mind that a property prediction model for continuous annealed steels produced at Tata Steel's plants in South Wales was developed. As continuous annealing is one of the final processes that strip steel undergoes before being dispatched to the customer the final properties of the strip are dependent on many factors. These include the annealing conditions, previous thermo-mechanical processing and the steel chemistry. Currently these properties, proof stress, ultimate tensile strength, elongation, strain ratio and strain hardening exponent, are found using a tensile test at the tail end of the coil.

This thesis describes the development of a model to predict the final properties of continuous annealed steel. Actual process data along with mechanical properties derived using tensile testing were used to create the model. A generalised regression network was used as the main predictive mechanism. The non-linear generalised regression approach was shown to exceed the predictive accuracy of multiple regression techniques. The use of a genetic algorithm to reduce the number of inputs was shown to increase the accuracy of the model when compared to those trained with all available inputs and those trained using correlation derived inputs.

Further work is shown where the fully trained models were used to predict the relationships that exist between the processing conditions and mechanical properties. This was extended to predict the interaction between two process conditions varying at the same time. Using this approach produced predictions that mirrored known relationships within continuous annealed steels and gives predictions specific to the plant that could be used to optimise the process.

Keywords: property prediction, continuous annealing, generalised regression network, genetic algorithm, sensitivity analysis.

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NOTATION

Proof stress	Re
Ultimate tensile strength	Rm
Elongation	A
Strain ratio	r
Strain hardening exponent	n
Basic oxygen steelmaking	BOS
Continuous annealing	CA
Radiant tube furnace	RTF
Controlled gas jet cooling	CGJC
Reheat overage	ROA
Overage	OA
Second cooling	2C
High gas jet cooling	HGJC
Hot Rolling	HR
Direct fire	DF
Carbon	C
Silicon	Si
Sulphur	S
Phosphorus	P
Manganese	Mn
Nickel	Ni
Copper	Cu
Tin	Sn
Vanadium	V

Nitrogen	N
Aluminium	Al
Niobium	Nb
Boron	B
Titanium	Ti
Chromium	Cr
Water Quench	WQ
Molybdenum	Mo
Arsenic	As
Calcium	Ca
Continuous annealing process line	CAPL
Zinc and other developments in alloy coatings	Zodiac
Mean square error	MSE
Root mean square error	RMSE
Mean percentage error	MPE
Correlation	R

CHAPTER 1 – INTRODUCTION

1.1. Novelty Statement

This thesis describes an investigation into the property prediction of continuous annealed steels based on their processing conditions. The work focused on the use of a generalised regression network, chosen following initial investigations into the use of regression and neural network approaches, as the main predictive method. Later this combined with a genetic algorithm to assist with input selection. The models' ability to identify the relationships between the input process conditions and output properties is also highlighted. The novelty in this work is as follows:

- A property prediction model relying only on actual processing conditions was developed for use with continuous annealed steels.
- A generalised regression network was used to facilitate these predictions, trained using data taken from online measurements and tensile tests.
- A bespoke training routine was developed to train these networks, relying on a genetic algorithm to optimise input selection.
- The relationships that exist between processing conditions and mechanical properties of continuous annealed steels were identified using fully developed prediction models. Coding based on the mean and standard deviation of the processing conditions facilitated this.
- The model was able to predict to a level of accuracy equal to that of other approaches which required addition measuring equipment or used laboratory based annealing data.
- Although initially developed to predict the properties of steels produced at Port Talbot the model's capabilities were extended to another line. This suggests that the

approach maybe suitably adapted for use within other areas of the steel industry, or indeed in different industrial applications.

1.2. Background

Tata steel is one of the world's leading suppliers of steel. Its customers cover a broad range of markets, such as construction, automotive, engineering and packaging. In 2007 Corus (now part of Tata Steel) produced approximately 4.3Mt of steel slab at its plant at Port Talbot. Of this, around 1.9Mt was processed in the cold mill [1]. Cold rolled products offer a solution to a wide range of problems. Typically, they find use in the following areas [2]:

- Automotive components and body panels
- Domestic appliances (white goods)
- Electrical goods
- Furniture
- Drums and radiators
- Tubes

Of these drums and radiators make up the largest share; accounting for approximately 280ktpa. Steel used in the automotive sector make up the second largest share, accounting for only 70ktpa [3]. A further breakdown of the main uses of Port Talbot produced continuous annealed steels is shown in Figure 1.1.

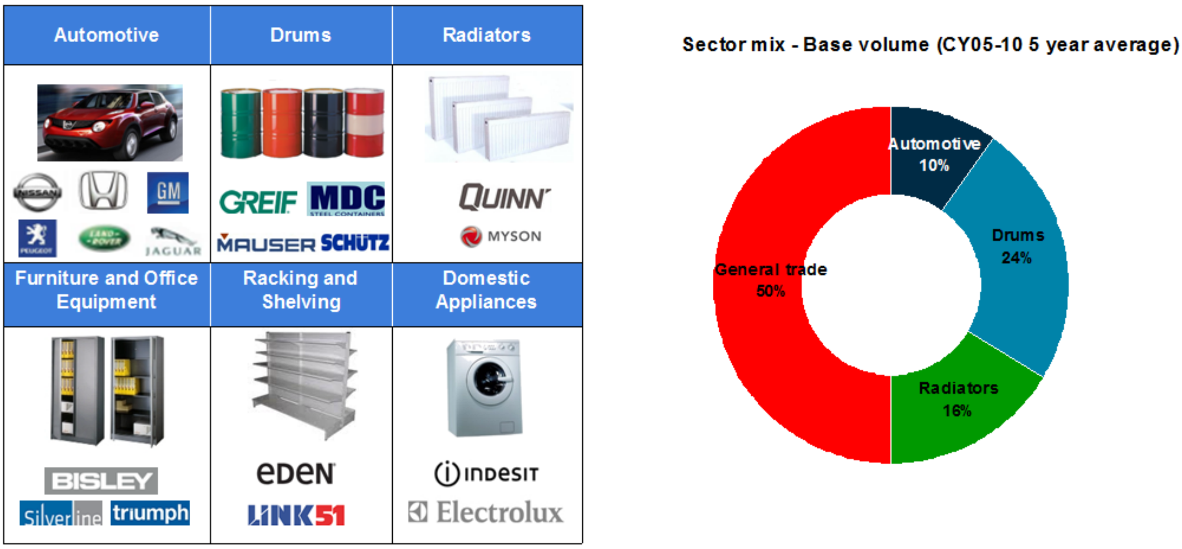


Figure 1.1: Sectors and customers supplied by CAPL (2005 to 2010)[4]

Many of these products require a high amount of formability. For this reason it is essential to anneal the cold worked material to give the required forming properties. Steel grades are chosen by the customer to meet their specific needs. Mechanical test data is needed from each coil to confirm that the coil is within the specifications of the customer and that it meets relevant standards.

Following the recent economic crisis, and thus fluctuation in demand for such products, as well as ever increasing customer demands the steel companies must strive for continual improvement in order to be competitive. Strong completion from other areas (particularly China) also means that European steelmakers need to be technologically advanced in order to offset cheaper labour costs. This means that new products need to be developed, quality improved and the production processes optimised. As annealing is one of the final processes that rolled steel undergoes it is an important area for continuous improvement. Optimisation of this part of the processing of steel could offer significant financial savings.

The final mechanical properties of continuous annealed steel are of great importance to customers and in some cases are required to meet release standards. Of particular interest are the proof stress (Re), ultimate tensile strength (Rm), elongation (A), strain ratio (r) and strain hardening exponent (n). These properties are affected by the variation in process conditions throughout the entire steel making process. In order to ensure that steels meet both the customers' requirements and any appropriate standards samples of each coil produced are taken for destructive mechanical testing. For the steels produced at Tata's plant in Llanwern this means a lengthy wait for results as there is no longer a test facility on the annealing line. This leads to problems releasing stock immediately, and thus has an associated cost. In order to overcome this problem an online method of finding the properties of the steel is needed. This methodology should work in real-time, negate the need for a destructive test and should produce results with sufficient confidence such that the need for physical testing is greatly reduced, with the ultimate aim of reducing the need for tensile testing entirely.

1.3. Project Objectives

The main aims of the project are listed below, along with a short description of each one.

- Produce a model which can be used to predict the release properties of certain grades of steel produced on the continuous annealing line at Port Talbot and Llanwern.
    - Currently release properties are calculated using a simple mechanical test. This project aims to replace this method with a predictive model that will use the processing conditions as inputs. Clearly the most important factors to consider are the accuracy of these predictions and the associated confidence levels. It is also important that customers should have confidence in the model and its workings.
- Produce a sensitivity tool to help identify the appropriate process window for the continuous annealing line at Port Talbot and Llanwern
    - The current process routes for continuous annealed steels are based on experimentation and the experience of those running the mill. Using the fully developed predictive model it is hoped that a method can be found to analyse the relationships between the process conditions and mechanical properties. These

relationships can then be used to identify the optimal process windows for the grades of steel under investigation. Such an approach may also be used to assess the implication of, and if necessary react to, varying slab compositions and upstream process variation.

1.4. Thesis Organisation

This chapter outlines the requirement for a property prediction model of continuous annealed steels to be developed based on economic factors and the product development needs. The research objectives for this project are also identified.

Chapter Two presents the background theory and a review of the available literature concerning this area of work. The details of how steel is produced at an integrated steel plant are followed by a more detailed review of the continuous annealing process and its alternatives. The properties under investigation in this work and the factors affecting them are then discussed. The need for data cleaning and an appropriate methodology are highlighted. Modelling philosophies and computational methods currently used in the steel industry are also covered. Finally, the details and theory behind generalised regression networks and genetic algorithms are discussed.

Chapter Three gives details of the initial data used in the modelling process and presents the work carried out to analyse the annealing process using a linear regression approach. Selection of inputs based on their correlation with the output properties is also considered.

Chapter Four covers the implementation of a generalised regression approach to predict the properties of continuous annealed steels. A comparison between these results and the previous linear regression models is included. The capability of the modelling approach is extended to other grades and annealing lines.

Chapter Five details improvements on the generalised regression network approach by combining it with a genetic algorithm for input selection. Two different approaches to this combination are proposed and the results from each are compared. The final modelling approach is then used to analyse all grades under investigation.

Chapter Six describes how fully trained models can be used to identify the relationships between input process conditions and the output properties. This technique can be applied to assess both the variation in a single factor and the effect of two variables changing simultaneously. The findings of this work are compared with known relationships to support the workings of the prediction models.

Chapter Seven summaries the findings of this study and discusses areas of potential further work and the direction it may take.

CHAPTER 2 – THEORETICAL BACKGROUND

2.1. Prior Thermo-Mechanical Processing

Continuous annealing is one of several processes that may take place during the production of steel. The main principle of it is to relieve the stresses which have built up in the steel during prior cold working. Continuous annealing is one of the final processes applied to steel produced at Port Talbot. This means that in order to gain a full understanding of the mechanics of the process and why it is necessary, the prior processes need to be considered.

At an integrated steel plant, such as Port Talbot, steel is produced by reacting iron ore with coke, which is carried out in blast furnaces. The iron ore is reduced by the carbon contained in the coke producing liquid iron with a high carbon concentration. The liquid iron is tapped from the furnace and delivered to the basic oxygen steelmaking (BOS) vessel. Here the excess carbon is removed in the form of carbon monoxide and carbon dioxide by blowing oxygen through the molten metal. The liquid steel is then sent to the secondary steelmaking stage, where the necessary alloying additions are made so that the required composition is produced and the steel grade meets the customer's demands. An illustration of the processing of low carbon steel strip, starting with the basic oxygen steelmaking vessel, is shown in Figure 2.1.

Following secondary steelmaking, the steel is then cast. Originally this would have been in the form of ingots, which were then rolled into slabs during a later process. Nowadays most steel plants have a continuous casting plant. Here slabs are formed directly. The liquid steel is poured into continuously oscillated water cooled copper moulds. The steel in contact with the mould solidifies, forming a skin. This is then drawn down through a gradually curved set of rollers until it is running horizontally. By this point the entirety of the steel will have solidified. Gas torches are then used to cut slabs to the required length. Slabs are then either sent to the marshalling yard or sent directly to the hot strip mill via a process termed 'hot connecting'.

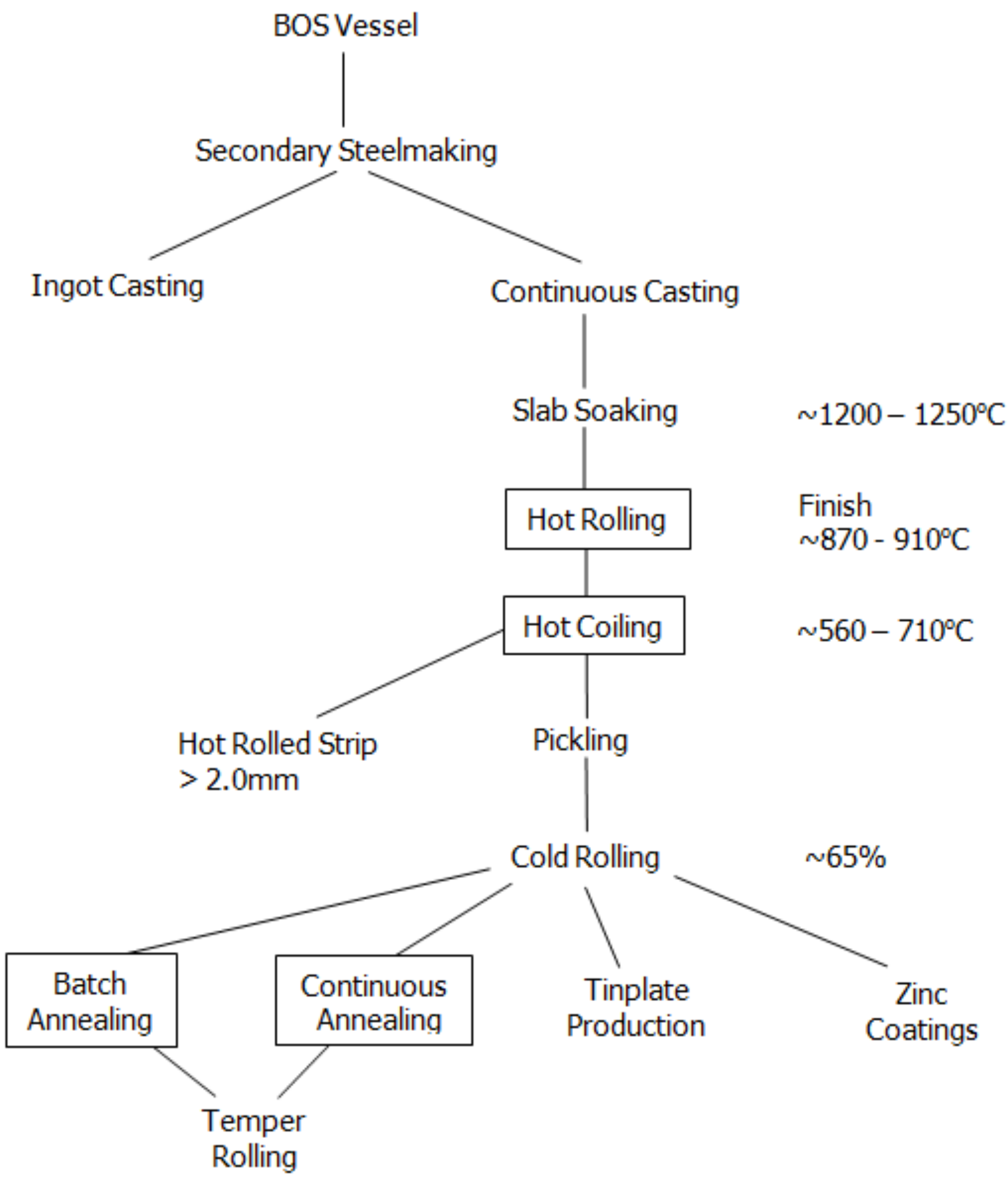


Figure 2.1: Process routes for low carbon strip steel [5]

At the hot strip mill slabs are first reheated to above the recrystallization temperature to around 1250°C. The actual temperature is dependent upon the slab's dimensions, the steel grade and later heat treatments [6]. Clearly slabs sent via hot connecting will require less energy to reheat them. The reheating of the slabs allows further working on them as the steel has been changed into the face centred cubic austenite phase. Due to the higher temperatures the strip can continuously recrystallise meaning they don't work harden. The slabs exit the furnace on to a conveyer system. During reheating a thick scale, caused by oxidation, will have built up on the surface of the steel. This is removed by scale breakers and high pressure water jets to prevent it being rolled into the coil leading to a reduced surface quality [7]. The slab then passes to the reverse roughing mill where the thickness is reduced to one closer to that required in the finished product. Slabs are approximately 234mm thick initially; the roughing process reduces the thickness to around 35mm [8]. Rolling takes place at about 60% of the absolute melting temperature, meaning work hardening does not occur as the steel recrystallizes at the same time [9]. At this point the slab is converted to what is termed a 'transfer bar'.

The transfer bar is then coiled in the coil box and the head and tail ends reversed. The coil box reduces the overall length of the hot strip mill as well as promoting homogenous strip properties by reducing temperature variation along the length of the strip [10]. The transfer bar is then uncoiled and passed through the finishing mill, entering at a temperature about 1050^{o}C [6]. At Port Talbot, this consists of seven four high roll stands which gradually reduce the thickness of the coil until it reaches the required size, from 2.5mm up to a maximum of 17.50mm [11]. The coil leaves the last stand at a temperature between 850^{o}C and 950^{o}C [6] and passes on to the run out table, where it is cooled under controlled conditions by a series of water jets.

At the end of the hot strip mill the strip is then coiled. It is important to point out that the temperature at the end of the finishing mill, the rate of cooling on the run out table and the final coiling temperature all have implications for the final structure and mechanical properties of the steel and so need to be considered for later property prediction.

Due to the elevated temperatures of the hot rolling process the surface of the steel will have once again accumulated scale. This scale must be removed prior to further processing so not to diminish the surface finish. This is done by a process called pickling. The coil is based through a bath of liquor containing either aqueous hydrochloric or sulphuric acid. The acid penetrates through cracks and defects in the surface of the scale and the associated reactions cause hydrogen gas to be evolved. The evolution of gas helps to further remove the scale by dislodging it from the coil's surface. The strip may then be washed to prevent further reactions from occurring.

The coil can then be cold rolled. During this process the thickness of the coil is further reduced by a series of five, four high, roll stands. The term 'cold' implies that the process takes place at temperature below the recrystallization temperature of the steel. Though no heat is input into the process, the strip temperature will rise due to the work exerted on it. The reduction in the coil's thickness occurs by means of dislocation movement. As the reduction continues, the dislocations within the material begin to pile up making it progressively harder to further deform the coil. For this reason the work exerted by each successive set of rollers needs to increase in order to produce the required deformation. As mentioned previously, the work exerted on the coil will lead to heating, however some of the energy is stored within the coil at the dislocations [6].

Coils that have undergone cold rolling will be very strong, due to the build up of dislocations. However their ductility will be greatly reduced, rendering them useless for forming operations. In order to rejuvenate the coil's ductility it must undergo an annealing process to relieve the stresses that have built up within the microstructure [6].

Annealing is primarily used to relieve stresses and increase the ductility of a coil that has undergone cold forming. The final mechanical properties and microstructure of the coil are heavily dependent upon it. Of these the formability, in particular drawability, is heavily dependent upon the annealing process as it is significantly influenced by the crystallographic texture [5]. Following cold rolling, a coil may then be processed by one of two major annealing techniques, batch annealing or continuous annealing.

2.2. Methods of Annealing

2.2.1. Batch Annealing

Batch annealing is an older technique used less and less in modern industry due to the time taken for the process to occur. It mainly finds a use as extra capacity or in cases when large ferrite grains are needed, as is the case with electrical steels. The process increases the formability of a coil that has undergone cold reduction whilst at the same time retaining some of its strength. A schematic of a typical batch annealing furnace is shown in Figure 2.2.

Coils are stacked three or four high on top of each other, separated by convector plates, in a bell shaped furnace. The interior cover is placed over the coils and its volume filled with inert gas to prevent the coils oxidising under the high temperatures. The outer furnace cover is put in position. Burners are fired tangentially at the inner cover causing it to heat up. Heat from this cover is radiated to the coils causing them to heat up too. The coils are then held, or soaked, at a temperature of around 650°C, just below Ac_1. The coils are then left to cool to room temperature. In order that the required temperature is achieved through the entirety of the coil, long heating, soaking and cooling times are employed. A typical batch annealing cycle is shown in Figure 2.3.

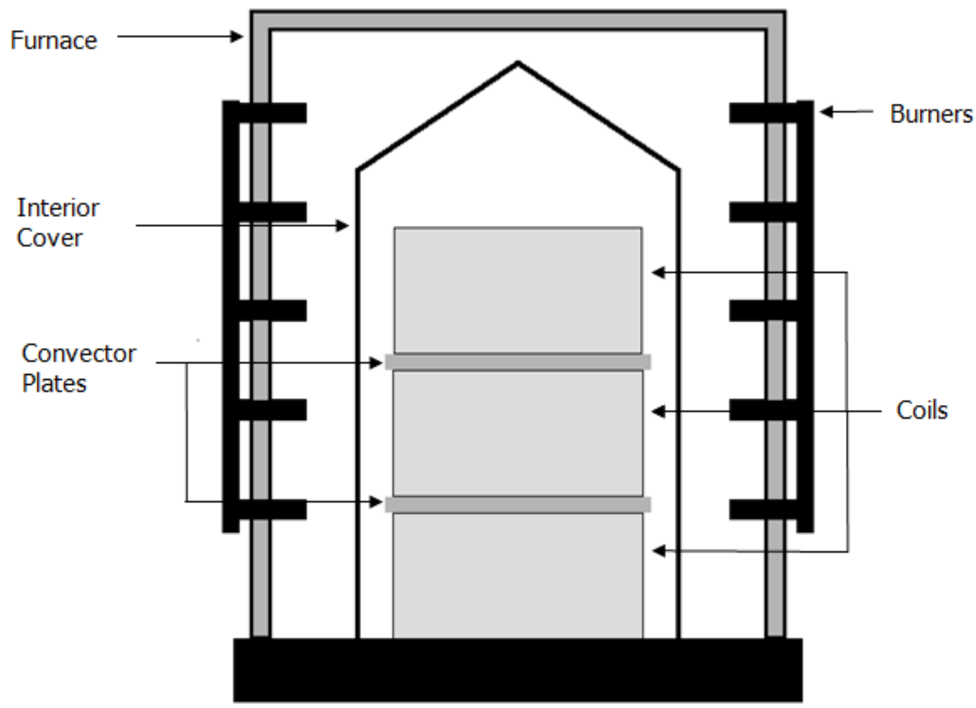


Figure 2.2: Batch annealing furnace schematic

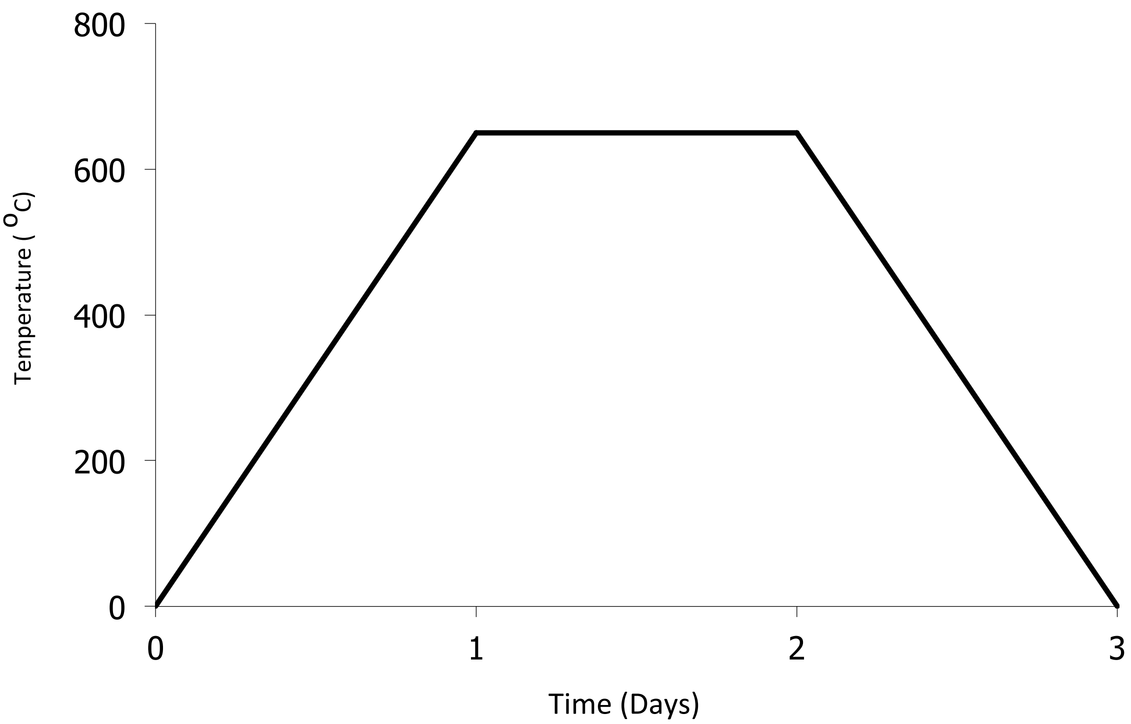


Figure 2.3: Typical batch annealing cycle

Recrystallization of the deformed structure begins to take place at temperatures around 550°C. This is by means of nucleation and growth of the nuclei. This process uses the stored energy within the grains and reduces the dislocation density. Prior to the coils reaching this temperature, aluminium nitride precipitates on the deformation sub-grain boundaries. The precipitates lead to a retardation of the recrystallization process by inhibiting nucleation of new grains leading to the final grains being large. The presence of the aluminium nitride also helps to produce the required texture for forming [5].

The coiling temperature of the coil during the hot rolling process is an important factor when considering the formation of the aluminium nitride precipitates. In the order that the aluminium is present in solid solution prior to the annealing process the coil temperature needs to be low. Typically a coiling temperature of about 560°C is utilised when a coil is to undergo batch annealing [5].

Grain growth continues during the soaking period leading to a relatively coarse grain size in the final product. A larger grain size could be achieved using a higher soak temperature but this is limited to around 730°C for two particular reasons. The first is that temperatures above this will result in the formation of coarse carbides which are detrimental to the formability of the coil. In addition, at elevated temperatures there is a greater chance of adjacent laps of the coil sticking to each other. At temperatures of around 700°C the ferrite microstructure contains the maximum amount of carbon in solution, approximately 0.02%. The slow rate of cooling employed will allow most of the carbon to have precipitated once the coil is at room temperature meaning that aging is not a problem [5].

The cooling rate can be adjusted so that some carbon will remain in solid solution. Upon further heating a strengthening of the steel occurs as the carbon in solid solution precipitates on any deformations. This process has found use within the automotive sector and steels with this property are said to be 'bake hardening'. This relates to the fact that the temperature required for the solid solution carbon to precipitate is close to the temperature needed to cure paint during an automotive painting process. Whilst the carbon is still in solid solution, pressings may easily be formed. The later painting and curing process allows this carbon to precipitate, resulting in the finished product showing an increased resistance to denting [12].

2.2.2. Continuous Annealing

Continuous annealing of steel strip was first introduced by the Armco Steel Corporation in 1936. The process was used as a step in the production of hot dip galvanized steel. Following its initial development, several developments have been made to the process that allow various steels, such as aluminized steel, tinplate and stainless steels, all to be processed via continuous annealing. Though there were several advantages offered by continuous annealing over the traditional batch annealing, including uniform properties, cleaner surfaces and a shorter processing time, it was not used for all applications due to its poor cold forming characteristics and poor resistance to aging. This problem was overcome in the 1970s when Japanese steelmakers introduced an overage stage into their annealing process that improved the problematic properties [5]. An illustration of the Continuous Annealing Process Line at the Port Talbot works is shown in Figure 2.4. This is a NSC (Nippon Steel Corporation) type line and was commissioned in 1999. The nominal output is 18800tonnes/week and a nominal speed of 130.34tonnes/hour [13].

Coils from the hot strip mill are loaded onto the de-coiler. As the process is continuous, the head of the new coil needs to be joined to the tail of the previous coil using a welder. In order to weld the two coils together, they both must be stationary. Stopping the line for this to occur would be impractical and would result in some sections of coil spending longer than others in the heat treatment section of the process. In order to overcome this problem a device called an accumulator is used, with one at the beginning and one at the end of the process. This consists of two parallel sets of rolls that can move apart from each other. As the entry accumulator moves apart it is able to hold more of the coil. When a weld is needed, the speed of the coil by the welder can slow down whilst the accumulator lowers, feeding the extra coil into the rest of the process and maintaining line speed. From the entry accumulator the coil passes into the furnace section. The coil passes through an entry seal roll into a non-reducing atmosphere. The first section of the furnace heats the strip to the required annealing temperature. Due to the high temperatures used, only steels with low carbon contents can be processed via continuous annealing. This is so the steel remains in the alpha range. Typically the carbon content will be below 0.015%. The reason for this is illustrated on the iron carbon phase diagram, shown in Figure 2.5. The range over which iron exists in the alpha form is very small but extends to the highest temperatures at the lowest levels of carbon.

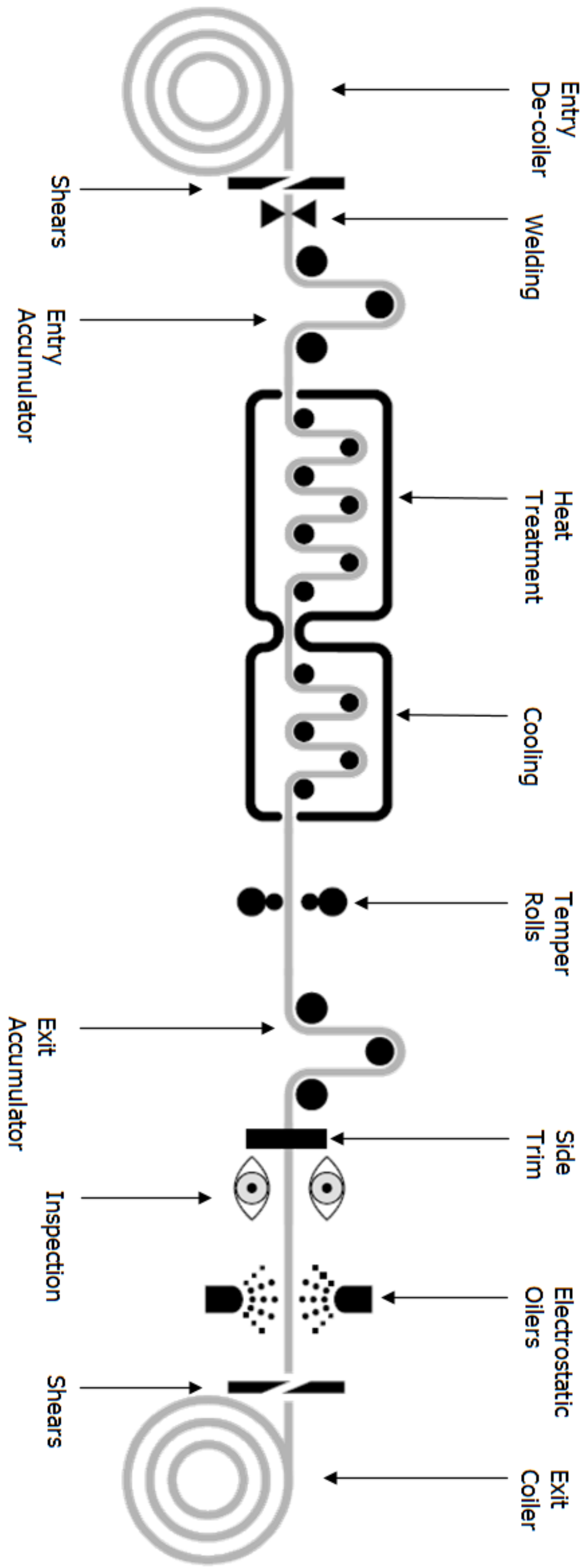


Figure 2.4: Major components of a continuous annealing process line [11]

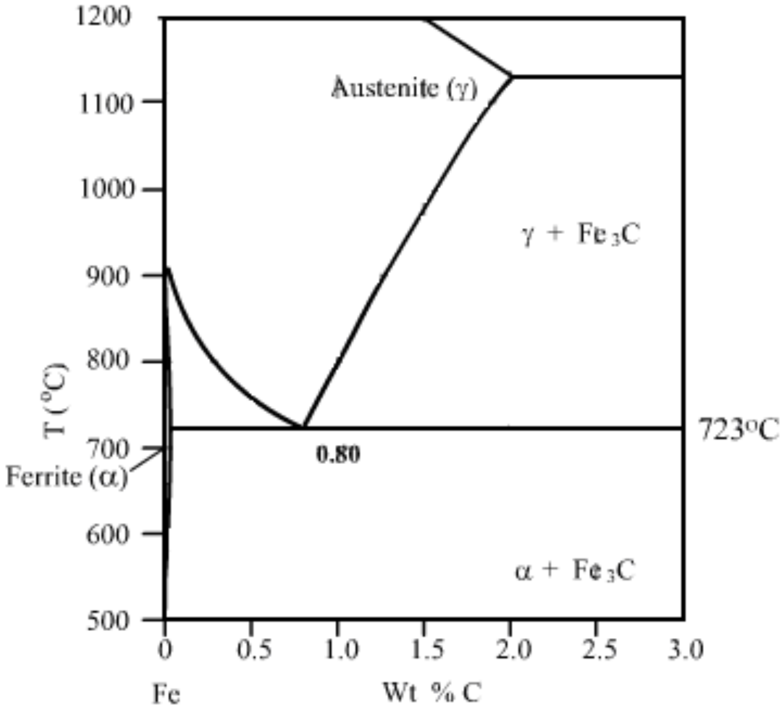


Figure 2.5: Iron carbon phase diagram [14]

The actual temperature that the steel is heated to and the rate of heating are determined by the steel's chemistry, prior processing and required properties. Details of the processing conditions of the steels chosen for this work are given later. The heating is provided by gas fired radiant tube heaters. Once the strip has been heated it then passes into the soaking section of the furnace. Here the steel is held at a constant temperature by electrical heaters. Once the steel has been held at temperature for a long enough time it is then cooled to a lower temperature so that the overage stage may begin. Initially, cooling is slow followed by a rapid cooling phase. Once cooled to a low enough temperature the overage process may begin.

In some cases a reheat overage stage may be needed. In these cases the steel is cooled to below the overage temperature in order to precipitate a greater amount of carbides within the microstructure of the steel. The steel is then reheated to the overage temperature. This allows the carbides to coarsen at a greater rate. Once the steel has gone through the overage stage it is slowly cooled back to room temperature. A typical continuous annealing cycle including a reheat overage is shown in Figure 2.6.

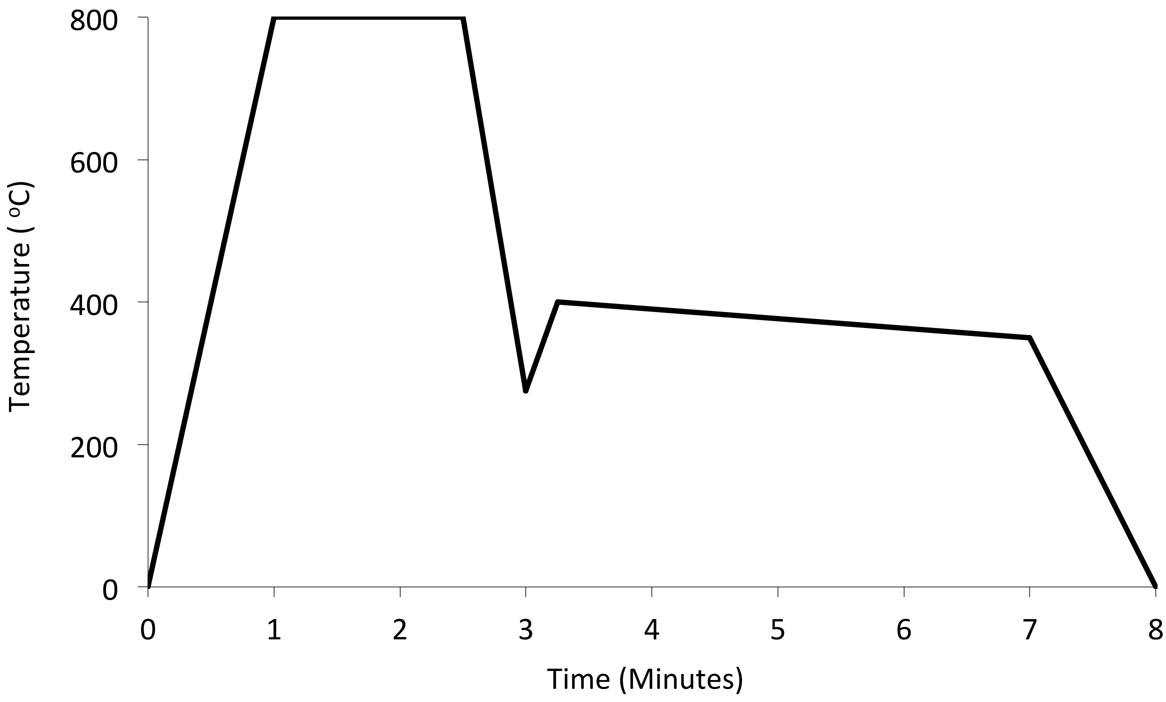


Figure 2.6: Typical continuous annealing cycle

The initial heating of the coil ensures it is at the correct temperature for the required annealing cycle. The rate at which the steel is heated may be varied, though the effects of heating rate upon the mechanical properties and microstructure of the steel are still relatively unknown.

During the initial heating of the coil, recovery begins to take place. Recovery refers to how a material changes prior to recrystallization, with some properties being partially restored to their value before deformation. Recovery is not one single change but rather a series of events. These include: dislocation tangles, cell formation, annihilation of dislocations within cells, sub-grain formation and sub-grain growth. It is not necessarily the case that all of these events will occur. This will depend on several parameters, including the deformation temperature and the annealing temperature. Some of these events may have occurred during the deformation process as dynamic recovery. The events normally occur in the order given but there can be a significant overlap between them [15].

The soaking period is where recrystallization takes place. One of the earliest attempts to rationalise recrystallization lead to the formulation of the laws of recrystallization by Mehl and Burke & Turnbill (cited in [15]). These are a series of statements based on a large body of experimental work. They are as follows:

- *A minimum deformation is needed to initiate recrystallization.* The deformation must be sufficient to provide a nucleus for the recrystallization and to provide the necessary driving force to sustain its growth.
- *The temperature at which recrystallization occurs decreases as the time of anneal increases.* This follows from the fact that the microscopic mechanisms controlling recrystallization are thermally activated and the relationship between the recrystallization rate and the temperature is given by the Arrhenius equation.
- *The temperature at which recrystallization occurs decreases as strain increases.* The stored energy, which provides the driving force for recrystallization, increases with strain. Both nucleation and growth are therefore more rapid or occur at a lower temperature in more highly deformed material.
- *The recrystallized grain size depends primarily on the amount of deformation, being smaller for large amounts of deformation.* The number of nuclei or the nucleation rate is affected by strain more than the growth rate. Therefore a higher strain will provide more nuclei per unit volume and hence a smaller final grain size.
- *For a given amount of deformation the recrystallization temperature will be increased by:*
    - *A larger starting grain size.* Grain boundaries are favoured sites for nucleation, therefore a large initial grain size provides fewer nucleation sites, the

nucleation rate is lowered and recrystallization is slower or occurs at higher temperatures.

- *A higher deformation temperature.* At higher temperatures of deformation, more recovery occurs during the deformation (dynamic recovery) and the stored energy is thus lower than for a similar strain at a lower deformation temperature.

Recrystallization is best described by breaking it down into two separate regimes, nucleation and grain growth. The laws of recrystallization are easily rationalised with this assumption. These terms are similar to those used to describe phase transformation and there is a superficial similarity between the two processes. The term nucleation when applied to annealing may not be strictly accurate but has become the accepted terminology [15].

Nucleation occurs within the sub-grains through a process called strain induced boundary migration. Within a deformed structure, the dislocation content is unlikely to be the same along both sides of a grain boundary. The result of this difference will be a bulging of part of the original grain boundary. This will leave a region behind the migrating boundary with a lower dislocation content. Eventually the bulging boundary becomes separated from its parent grain leaving a strain free grain. The dislocation storage rate depends on grain orientation and may be different at the boundary regions allowing strain induced boundary migration to occur. The new grains produced have a similar orientation to their parent grains [15, 16].

In order to produce homogenous properties within a coil, grain growth and final size need to be uniform. This means that the grain growth phase is an important stage in producing the final required properties. During this stage the nuclei formed by strain induced boundary migration grow with the driving force being the reduction in grain boundary energy. There are two variations of grain growth, normal and abnormal [15].

As the title suggests, normal grain growth implies that grains grow in a uniform manner. There will be a narrow range of grain sizes and shapes, leading to uniform properties throughout the coil. Growth continues steadily until neighbouring grains impinge each other. This results in a structure of equiaxed grains. Growth of this manner may be represented using the Avrami equation which is discussed later [15, 16].

With abnormal grain growth, some grains will grow in preference to other grains. This will result in a variety of grain sizes and shapes, leading to non-uniform properties in the coil. Abnormal grain growth will eventually lead to the larger grains impinging each other and normal grain growth returning. Abnormal grain growth is likely to occur when there is at least one strong texture component [15, 16].

The coil then passes into the cooling section of the furnace. The coil is cooled to the overage temperature. The overage stage involves holding the strip at a temperature significantly below the recrystallization temperature to achieve equilibrium between the ferrite and cementite. This allows carbon in solution to precipitate at preferential sites, due to the lower solubility of carbon at the overage temperature than the annealing temperature. This leads to a reduction in the aging effect on the steel. If this stage was not included there would be fine carbide precipitates throughout the coil which would be detrimental to its formability. The formation of larger carbides has less of an effect, as there are fewer of them, on the formability [17]. In some cases the coil will be cooled below the desired overage temperature. Doing so allows for more carbon to precipitate. The coil is then reheated to the overage temperature to allow the newly formed carbides to coarsen.

During batch annealing, aluminium nitride precipitates whilst the coil is being slowly heated. The fast heating rates of the continuous annealing process do not allow this to happen, meaning that nitrogen would remain in solid solution. The result of this would be a coil with increased strength with reduced formability and increased susceptibility to aging. In order to alleviate this problem, coils that are scheduled to undergo continuous annealing are coiled at a higher temperature, around 710^{o}C, at the end of the hot rolling process. This allows the material to cool slowly through the range of temperatures that are preferential for aluminium nitride precipitation [5].

Upon exiting the heat treatment section of the continuous annealing process line the coil then passes through the temper mill. This is another rolling process. A single roll stand applies a small reduction, approximately 0.8% to 1.5%, to the coil [18]. This is done for two principle reasons. The first is to remove the phenomenon of discontinuous yielding.

In cold worked steel, dislocations lead to a distortion on the lattice structure. The energy related to this distortion can be reduced by the presence of solute atoms, such as carbon or nitrogen. The presence of these solute atoms means that moving these dislocations, through further processing of the material, will be impeded and requires a greater strain. Once the dislocations have been separated from their associated solute atoms the strain required to move them is reduced [19]. Discontinuous yielding is illustrated in Figure 2.7.

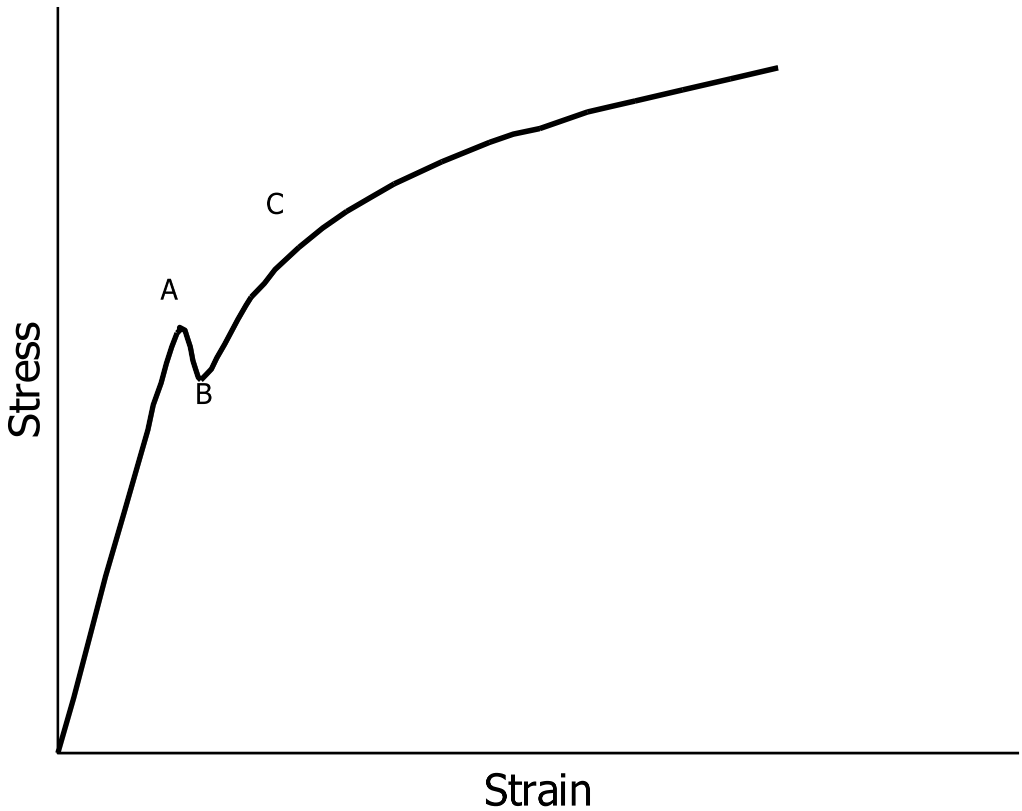
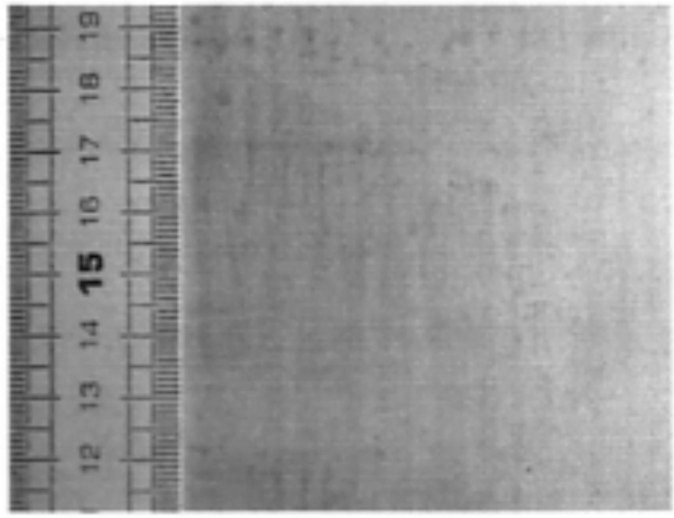


Figure 2.7: Illustration of discontinuous yielding

The yield point, A, represents the stress required to move the dislocations from the solute atoms. Point B represents the stress required to continue moving the dislocations. The end result of this is that products undergoing a forming process may suffer from non-uniform localised deformation, leaving stretch marks, or Lüder's bands, on the surface as illustrated in Figure 2.8. The temper rolling negates this problem by applying a compressive deformation to the steel, meaning that the marks will not be present. This would stress the material to point C in Figure 2.7 meaning that no further yielding would occur during subsequent forming. Leaving the material as stock for a long period of time or applying a heat treatment would allow the solute atoms to return to the dislocations meaning the yield point returns [19]. This phenomenon is known as aging.

(a) Lüder's bands on a tensile specimen



(b) Stretch-Strain marks on under tempered strip

Figure 2.8: Illustration of Lüder's Bands [18]

The second reason for the temper mill is to control the surface finish of the strip. It ensures that the strip is flat and allows for any required surface texture, for example to allow for the application of a coating, to be imparted on the coil [18]. It is important to note that the tempering process occurs after annealing. Should any property prediction model be produced with the intention of utilising it online as a corrective tool, investigation into the effects on properties due to temper rolling will need to be undertaken.

After temper rolling, the coil enters the exit accumulator. This allows the strip speed to be controlled as it passes through the side trimmers, inspection, oiling and shears. The coil is then rewound in the exit coiler. Samples of the tail end of the coil will be taken to allow for testing to be carried out. The coil is then wrapped to allow it to be stored. From here it may be sold to a customer as an uncoated product or sent for further processing so that a metallic or paint coat can be applied. The continuous annealing process line offer coils with a minimum thickness of 0.38mm and a maximum thickness of 2.00mm [20].

2.2.3. Comparison of Batch and Continuous Annealing

The introduction of continuous annealing within the steelmaking process has allowed for the development of many novel grades of steel. The speed of the process and scope for improvement has meant that continuous annealing has risen to the treatment of choice within industry even though there is a significant cost associated with its installation, upwards of $150million compared to $25million for a batch annealing system [21]. There are several reasons for the increased use of continuous annealing systems, for example [21, 22]:

- The integration of several processes into one continuous line, e.g. degreasing and temper rolling
- The development of new products such as advanced high strength steels which have limited scope to be produced via batch annealing
- Processing time is much quicker; coils produced via continuous annealing can be processed in around ten minutes where as batch annealing steels may take three days
- Product quality is much better with homogeneous properties along the length and width of the coil, along with better edges and reduced waviness

2.3. Properties Under Investigation

2.3.1. Measurement Methods

The final mechanical properties of the steel produced must meet the specifications of the customer and those set by any relevant international standards. Preparation of samples and the testing methods are currently governed by the criteria specified in BS EN ISO 6892-1:2009 [23]. At Port Talbot samples are tested offline, though the test house facility is housed in the same area.

Samples are taken from the tail end of the coil, just before the weld. The shears make a cut that becomes the end of the first coil. A second cut is made to produce a small sheet of steel, with the rest then forming the next coil. The test sample is then delivered to the test house; as this is an automated process, the details of the current coil are already available to the workers there. Three test pieces are produced at 45^{o} to each other by means of a press. Unless stated otherwise, only the test piece taken in the transverse direction is used. The size of the test piece is set out in BS EN ISO 6892-1:2009. Details of the test piece are shown in Figure 2.9 and described in Table 2.1.

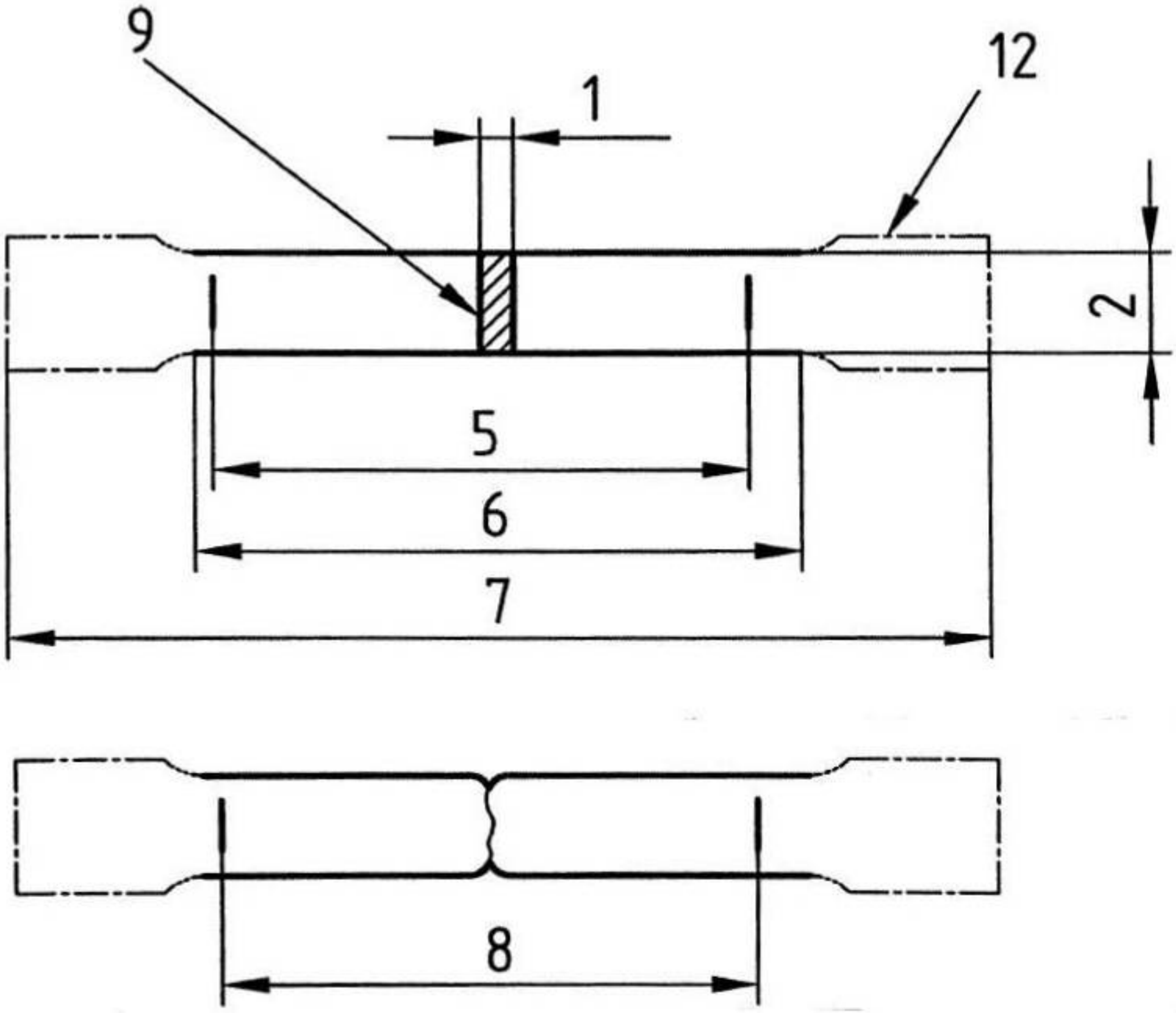


Figure 2.9: Details of standard tensile test piece

Table 2.1: Details of standard tensile test piece (from Table 1 of BS EN ISO 6892-1:2009)

Reference Number	Symbol	Unit	Designation	Nominal Size
1	a_O	mm	original thickness of a flat test piece or wall thickness of a tube	
2	b_O	mm	original width of the parallel of a flat test piece or average width of the longitudinal strip taken from a tube or width of flat wire	1. 12.5 ± 1 2. 20 ± 1 3. 25 ± 1
5	L_o	mm	original gauge length	1. 50 2. 80 3. 50
6	L_c	mm	parallel length	1. 57(min) 75(recommended) 2. 90(min) 120(recommended) 3. 60
7	L_t	mm	total length of test piece	
8	L_u	mm	final gauge length after fracture	
9	S_o	mm^2	original cross-sectional area of the parallel length	
12	-	-	gripped ends	

This is fed into an automated process that produces a standard stress/strain curve on a computer, as shown in Figure 2.10. From this the necessary properties of the coil can be extrapolated. These details, described below, are recorded and logged with the other data associated with that coil. Should the first test fail (suggesting the material is out of specification) a second sample may be tested. Should this fail the coil may be offered to the customer at a reduced price along with the associated test results. Alternatively the coil may be downgraded to one where the mechanical properties are within a tolerable range and sold to another customer. Samples may be taken to the main test house should further testing be required.

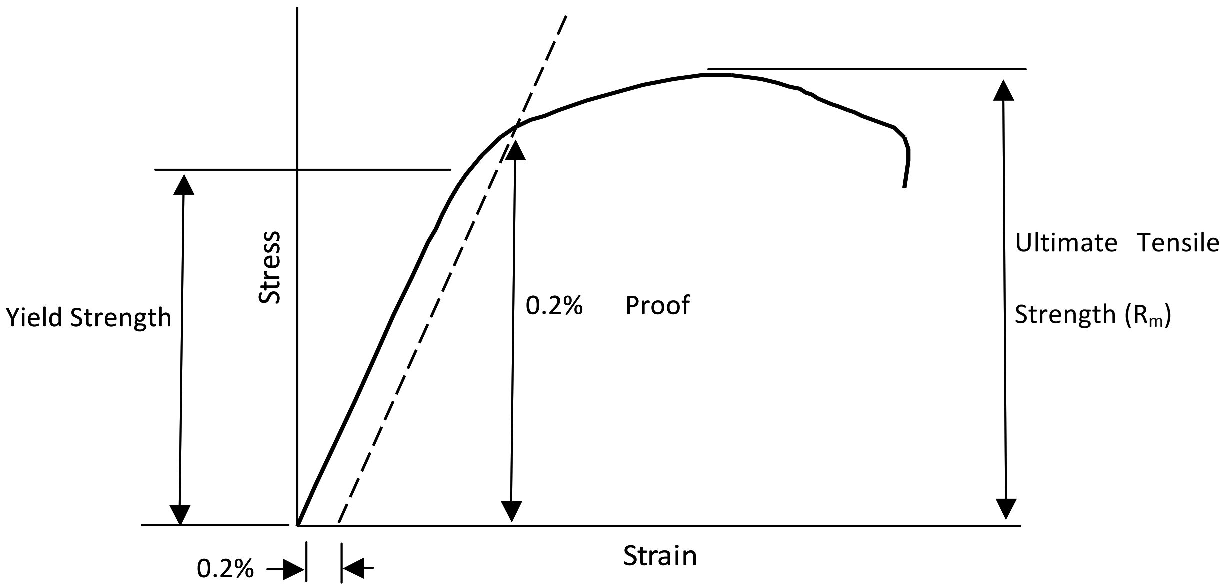


Figure 2.10: Typical stress/strain curve formed by tensile testing

2.3.2. Proof Stress

Proof stress, Re, is defined as the minimum stress required to produce a permanent plastic deformation. In order to gain comparable results this is normally defined with a specific amount of plastic strain, dependent upon material or specifications. Typically an offset of 0.2% is used, known as the proof stress.

2.3.3. Ultimate Tensile Strength

The ultimate tensile strength, Rm, may be found by taking the maximum load experienced by the steel and dividing it by the initial cross sectional area of the sample. This may be seen as the minimum stress that will result in the sample failing, as well as giving a good indication of the material's toughness.

2.3.4. Elongation (A)

The elongation is a measure of the ductility of the material. It represents the change in length of the material during the tensile test and is found by dividing the change in axial length after fracture by the original length. Plastic deformation will be concentrated around the necked region of the specimen. This means that the elongation value is dependent upon the gauge over which the measurement was taken. Using a smaller gauge will result in larger strains in the necked region. It is therefore important to quote the gauge used for measurement.

2.3.5. Strain Ratio (r)

The steels chosen for this investigation are used specifically in applications where their formability is of key importance, particularly deep drawing and stretch forming. Deep drawing is where material flows into a die under pressure, as shown in Figure 2.11.

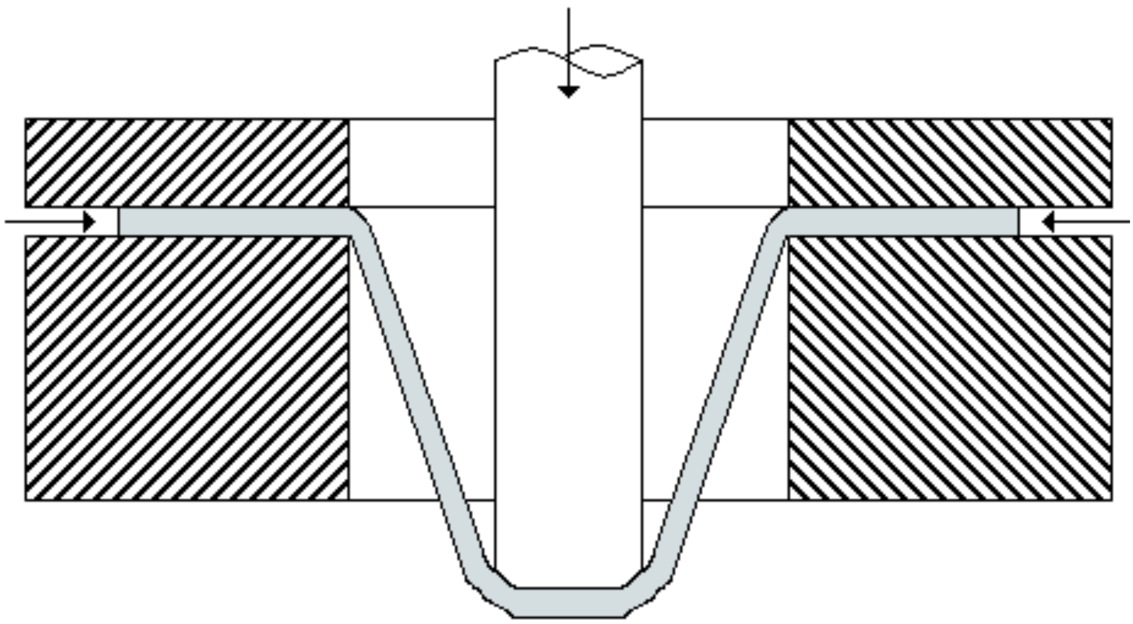


Figure 2.11: Illustration of deep drawing

Steels chosen for this application need to flow easily in all directions and show resistance to local thinning in the side walls during elongation. This was quantified by Lankford et al [5] when the concept of the strain ratio (r value) was developed. This concept expresses the plastic anisotropy of a material as the ratio of the true strain in the width to the true strain in the thickness of a specimen in a tensile test.

$$r = \frac{\varepsilon_w}{\varepsilon_t} \tag{2.1}$$

The strain ratio is related to the crystallographic texture of the material, thus there will be variation in the result depending upon the direction that test sample was cut in relation to the rolling direction. In order to show the average properties of the sheet, several samples are cut from it. They are taken parallel, transverse and at 45° to the rolling direction. Using the equation below, the average plastic anisotropy, $\bar{r}$ can be found.

$$\bar{r} = \frac{r_l + 2r_{45} + r_t}{4} \tag{2.2}$$

Hot rolled strip has an average plastic anisotropy of about 1, showing that it is isotropic [5]. For the material to be used in complex forming operations it needs to resist thinning. These properties are present in a material with a well developed crystallographic texture such as that found in annealed steel, which is shown by a higher $\bar{r}$ value.

2.3.6. Strain Hardening

Stretch forming requires that the material is held to prevent it flowing into the die. A punch is used to deform the metal by means of elongation so that it forms the desired shape, this can be seen in Figure 2.12.

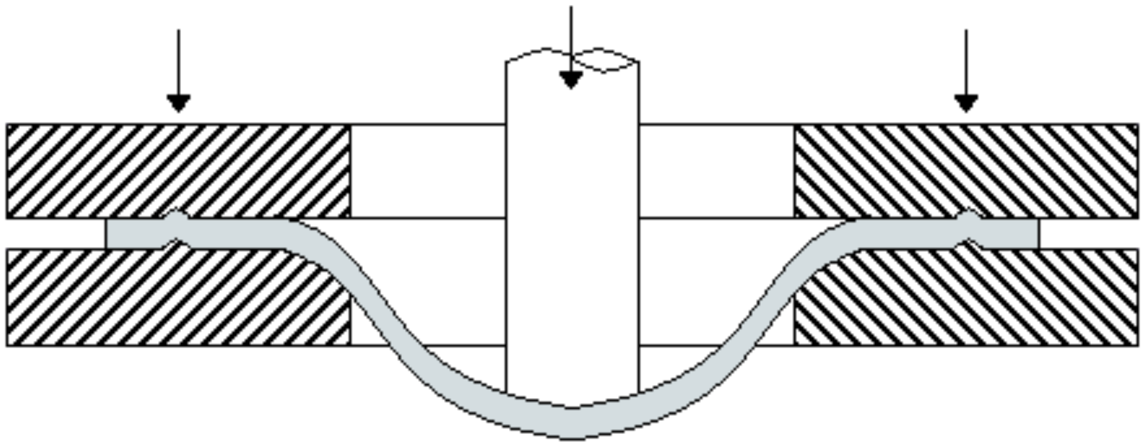


Figure 2.12: Illustration of stretch forming

Clearly steels formed in this way need to withstand large amounts of uniform elongation before they start to thin, or necking or fractures occur. In order to gain an indication of the behaviour of steel under these conditions, one may use the strain hardening exponent (n value), sometimes called the work hardening coefficient. This represents the gradient of the true stress versus true strain curve in a tensile test when plotted on a logarithmic scale [5]. This relationship conforms to a reasonably straight line allowing the following equation to be produced:

$$\sigma = k\varepsilon^{n} \tag{2.3}$$

Where σ is the true stress, ε is the true strain and k and n are constants. It can be shown that n is numerically equal to the uniform elongation [5].

Steels with good formability have higher n values, for example cold-rolled materials will have n values in the range of 0.22 to 0.25. Hot rolled materials may have n values of about 0.1. Pressings of these materials will result in excessive thinning and the possibility of fracture in heavily strained areas. The work hardening of materials with high n values is sufficient enough to transfer strain from critical areas to adjacent ones in order to avoid high concentrations of strain [5].

2.4. Property Relationships

In order to model the mechanical properties mentioned in the previous section, one must first understand what factors affect them. These will include, for example, the microstructure of the steel, processing conditions and the steel chemistry. This section describes these factors. Possible methods of relating these factors to the mechanical properties they affect have been highlighted.

2.4.1. Early Developments

Steel making, including deformation and heating, has been practised for many thousands of years. Only recently have the structural changes associated with these processes begun to be understood. This sudden change in pace is linked to the development of material characterisation techniques, indeed this is still the case today [15].

This first recorded evidence for structural changes occurring during the annealing of cold worked material was in 1829. Felix Savart, a French physicist, noted that the acoustic anisotropy of cast ingots changed upon deformation and subsequent annealing but not upon heating alone [15]. The inability of early metallurgists to observe grain structure gave rise to the belief that plastic deformation rendered metals amorphous. Upon reheating, the grain structure could sometimes be seen, leading to the idea that this was crystallization of the steel from the amorphous state.

Sorby's introduction of metallographic techniques allowed the observation of elongated deformed grains in iron and the subsequent production of an equiaxed grain structure upon heating. This he termed recrystallization. He also made the link that distorted grains were unstable and that they returned to a stable state through recrystallization.

2.4.2. Factors Affecting the Strength of Steel

There is a vast quantity of work that aims to quantify the relationships that exist between the mechanical properties of steel and the processing conditions and physical appearance. This section reviews those thought to be most relevant to continuous annealing. Although the relationships themselves may not be relevant to this work, some of the factors chosen may highlight areas that are important to this research.

Refining the grain size is one of the most important heat treatments of steels. The relationship between grain size (d) and yield strength (σ_y) was first modelled by Hall and Petch, producing the classic Hall-Petch relationship [24, 25]:

$$\sigma_y = \sigma_o + k_y d^{-\frac{1}{2}} \tag{2.4}$$

Where σ_o and k_y are constants representing the frictional stress and slope respectively. The frictional stress is seen to be the stress required to move free dislocations along slip planes in a body centred cubic structure. It is sensitive to temperature and composition. The slope, or resistance of grain boundaries to dislocation movement, is found not to be sensitive to temperature, composition or strain rate [26].

From this equation it can be seen that finer grain sizes result in a higher yield stress, explaining why there is a strong focus to reduce the size of grains within modern steel plants. In order to quantify the grain size and rate of growth, an understanding of the kinetics of recrystallization is needed.

A common approach to modelling recrystallization is through use of the Johnson-Mehl-Avrami-Kolmogorov (JMAK or Avrami) model [27]. This approach is based on work by Kolmogorov [28], Johnson and Mehl [29] and Avrami [30]. This model focuses on a general form of recrystallization, as shown in Figure 2.13 (based on [31]).

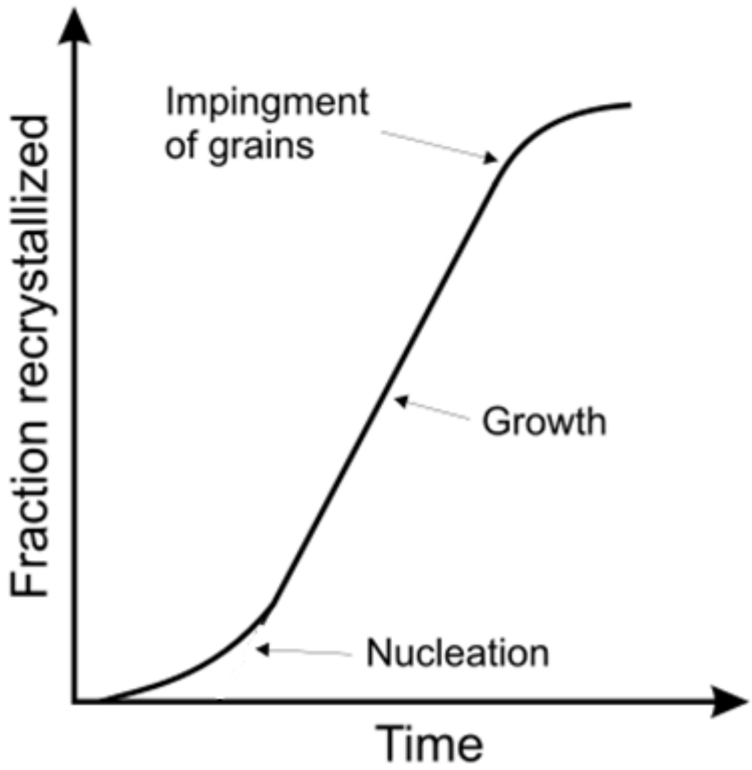


Figure 2.13: Illustration of recrystallization

In this case it is assumed that nuclei are formed at a rate of $\dot{N}$ and that grains grow into the deformed material at a linear rate $\dot{G}$. If the grains are assumed to be spherical, their volume varies with the cube of their diameter. The fraction of recrystallized material (X_V) rises rapidly until new grains impinge each other. As X_V approaches 1, the rate of growth will tend to zero. This gives rise to the general equation:

$$X_V = 1 - \exp(-Bt^n) \tag{2.5}$$

where:

$$B = f\dot{N}\dot{G}^3/4 \tag{2.6}$$

In equation 2.6 f is the shape factor (for a sphere this is 4π/3). The n in equation 2.5 is the JMAK exponent. In the case above, where growth is considered in three directions, n has a value of 4. This assumes that the nucleation and growth rates remain constant. The other extreme considers the situation when the nucleation rate decreases so rapidly that all nucleation events occur at the start of recrystallization, termed site saturation nucleation. In this case the exponent value will be 3. Further details of this derivation can be found in Humphreys and Hatherly [15].

The JMAK model alone is not detailed enough to fully define the kinetics of grain growth. Other factors must also be considered. Higgins [19] suggests that some of the main factors that grain growth is dependent upon are:

- The annealing temperature used, with larger grains growing at increased temperature.
- The duration of the annealing process, with initial rapid growth being followed by slower growth.
- The amount of previous cold work. Larger amounts of deformation will result in several areas with high levels of stored energy. Following the nucleation process described earlier, this will lead to many nuclei being formed and hence the final grain size will be small.
- The use of alloying elements within the metal. Certain additives will limit grain growth, nickel being one example. Insoluble particles may also act as a barrier to grain growth.

Evans et al [32] attempted to model continuous annealed aluminium killed steels, similar in nature to the boron killed steels under investigation in the current project. In their study of the recrystallization kinetics they found that increased amounts of free nitrogen prior to annealing led to its retardation. This they linked to the solute nitrogen particles impeding dislocation movement during the recovery process. The same retardation effect was also seen in batch annealing steel investigated by Takahashi & Okamoto [33].

Though nitrogen has been seen to retard recrystallization, the authors report that the free nitrogen content is not a factor affecting the grain size at the end of recrystallization. Instead the carbon content of the steel was found to influence the recrystallized grain size. Evans et al also observed the relationship between grain size and annealing soak temperature. Their results can be seen in Figure 2.14.

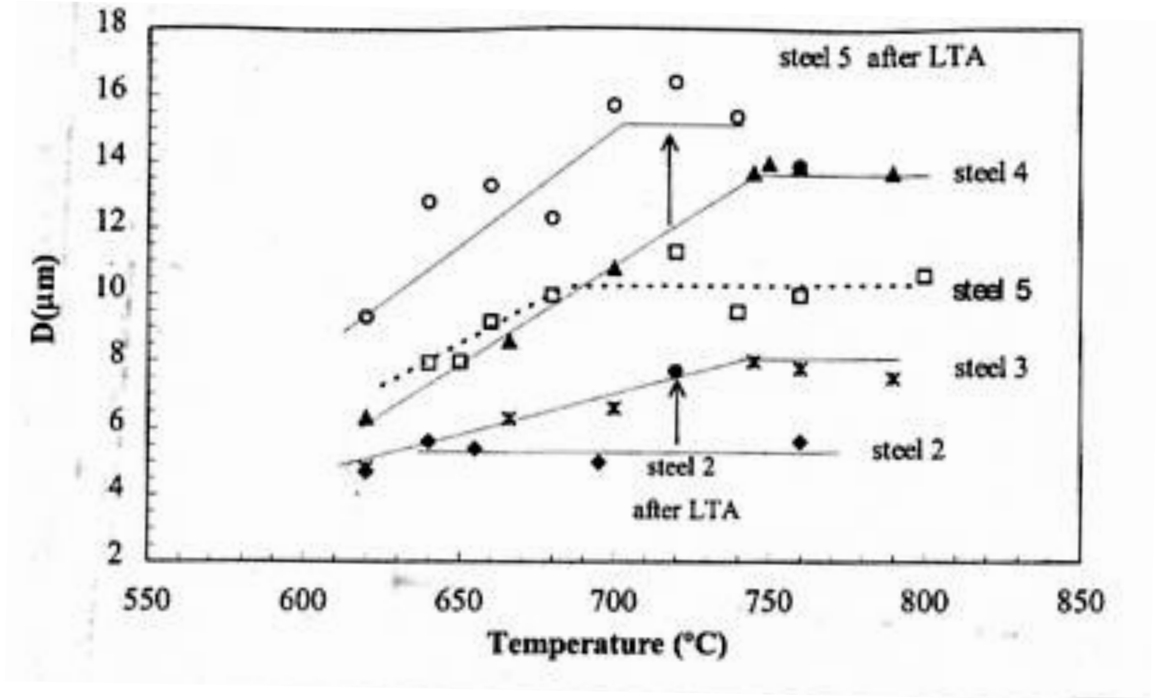


Figure 2.14: Grain size as a function of the annealing temperature [32]

The decrease in grain size at higher temperatures was related to the formation of austenite which transformed back to ferrite upon cooling, thus refining the grain size.

2.4.3. Factors Affecting the Formability of Steel

The steels under investigation in this report are required to be formable. In order to obtain good drawing properties the correct texture needs to be produced. This has been found to be the {111} texture, also known as the γ-fibre. This texture ensures that the slip systems are orientated in such a way that strength in the thickness direction is greater than that in the plane of the sheet [34]. Figure 2.15 shows this and other textures in a standard unit cell. Higher r-values correspond to a high proportion of grains aligned with the (111) plane which run parallel to the surface of the strip.

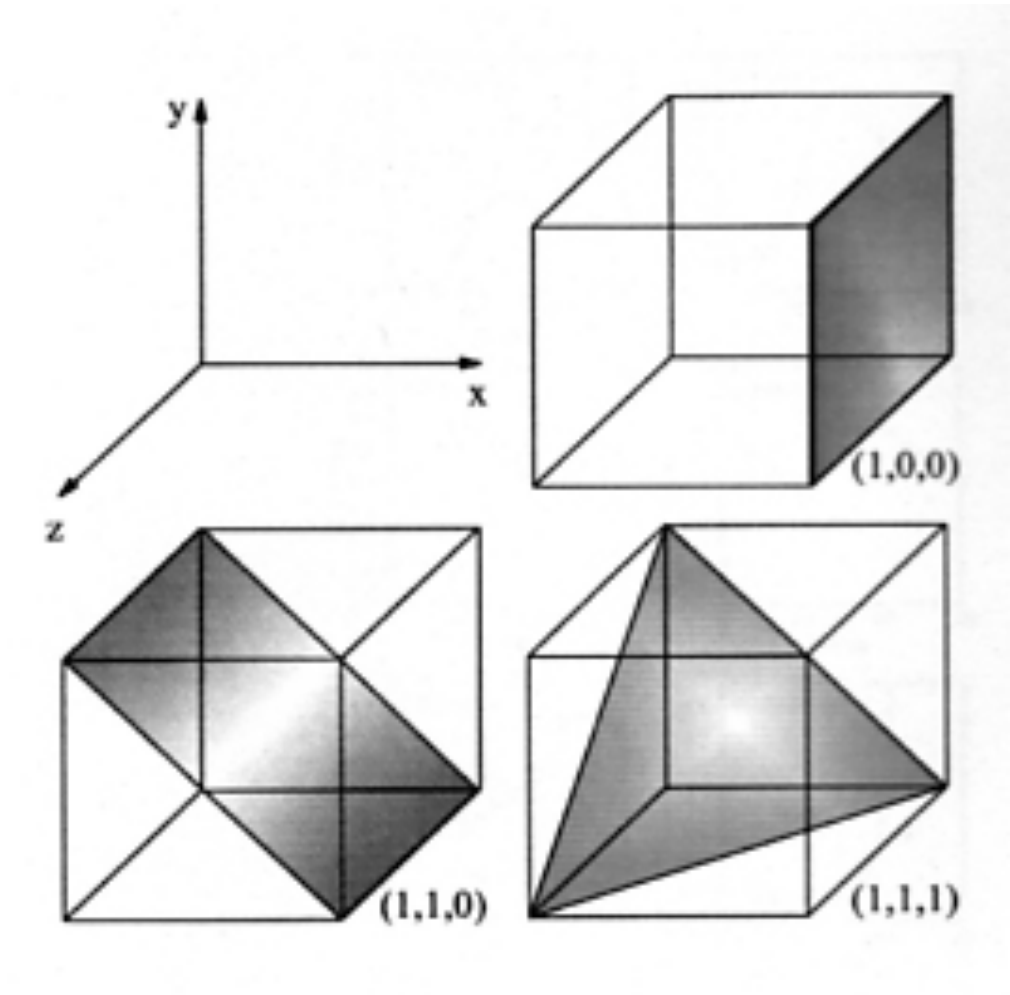


Figure 2.15: Textures within a unit cell [18]

The development of the final texture is a continuous process with the outcome being influenced by the development of the texture during the different processing phases, i.e. hot rolling, cold rolling and annealing. As one would assume, the processing parameters required to obtain the desired texture depend upon the type of steel being produced. It should also be noted that the annealing method used has a significant influence on prior processing conditions. An example of this may be the coiling temperature used. As described earlier in this report, batch annealing requires coiling to occur at lower temperatures than equivalent steels produced using continuous annealing so that aluminium is present in solid solution [35]. Held (cited in[32]) suggests an empirical relationship between the {111} texture component and the average plastic isotropy. This is given by:

$$\bar{r} = 0.8 + 0.6 \mathrm{Log}(I\{111\}/I\{100\}) \tag{2.7}$$

The quotient I{111}/I{100} represents the ratio intensity of the two textures. This ratio changes with grain size. Evans et al [32] considered the relationship between this and grain size. Their final relationship related the ratio to the difference between final grain size, D, and the grain size at the end of recrystallization, D_{rec}. Their results fell into two categories: those with extra low carbon contents and those with ultra low carbon contents. These could be described using two separate equations.

Extra low carbon steels: $$I\{111\}/I\{100\} = 1.6 + 0.2(D - D_{rec}) \tag{2.8}$$

Ultra low carbon steels: $$I\{111\}/I\{100\} = 6.3 + 2(D - D_{rec}) \tag{2.9}$$

The lower values that would be obtained from the extra low carbon equation relate to the higher carbon content of this type of steel. The carbon is in solution and is likely to inhibit the development of a strong {111} texture. The ratio I{111}/I{100} was observed to increase during recrystallization and then continue during grain growth. This results in a more favourable texture being produced which is independent of grain size [32].

The texture of the steel can also be related to the amount of cold reduction. Work carried out by Pero-Sanz et al [35] investigated what influence the amount of cold reduction had on the drawability of steel. In the investigation low carbon steel and interstitial free steel were studied. The steels under investigation underwent varying degrees of cold reduction, ranging from 0 to 90%. The intensity of certain texture components were compared with the level of reduction. These results are shown in Figures 2.16 and 2.17.

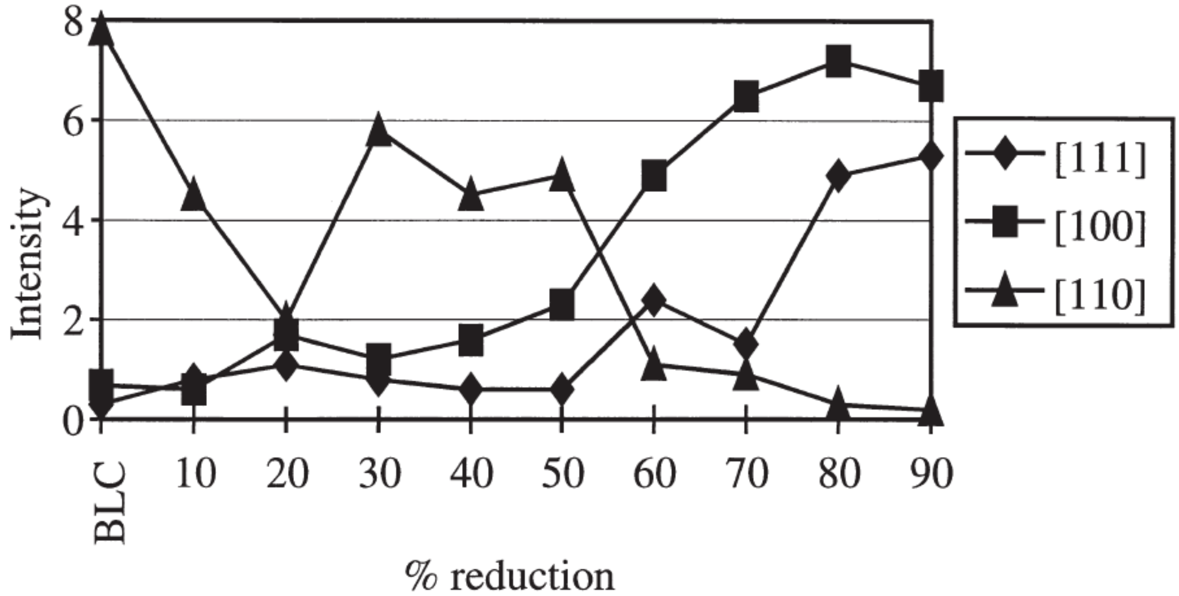


Figure 2.16: Interstitial free steel rolled texture [35]

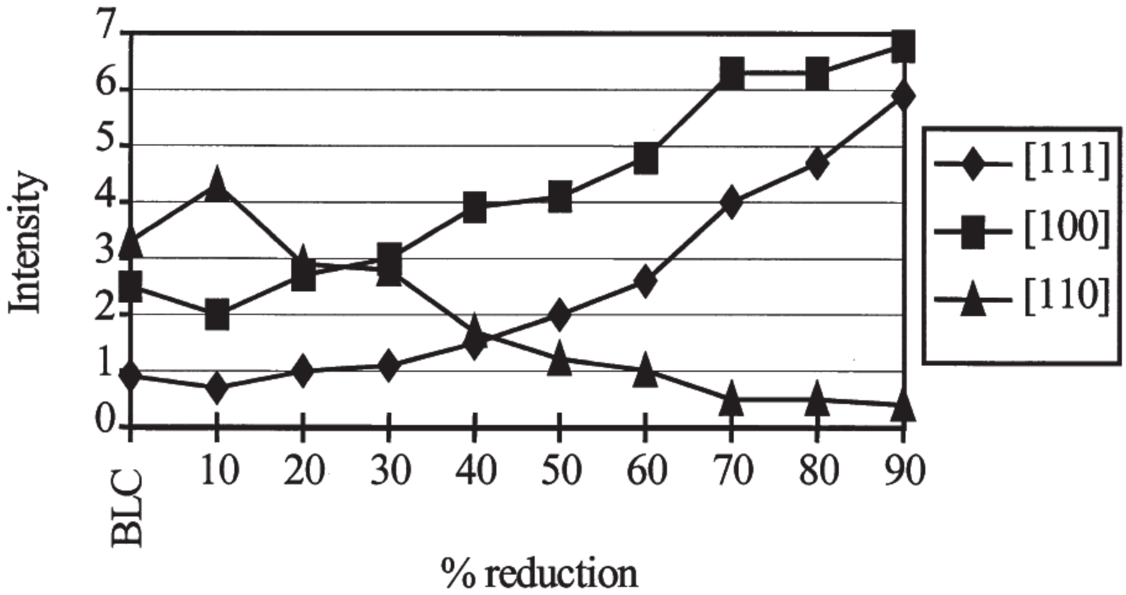


Figure 2.17: Low carbon steel rolled texture [35]

The results show that increasing the amount of cold reduction leads to a better texture for drawability. These results match those found by other researchers [32, 36]. These results can be attributed to the stored energy within the steel's microstructure. When a steel undergoes cold deformation, the majority of the work expended is given out as heat, with only a small amount (about 1%) remaining within the material. This stored energy comes about from the point defects and dislocations formed by the deformation. Annealing allows these high energy areas to recover to a low energy state through the mechanisms of recrystallization and grain growth [15].

The orientation changes due to deformation are not random. Deformation occurs on the most favourable slip or twinning systems meaning the deformed metal acquires a preferred orientation or texture. During subsequent annealed nucleation occurs preferentially in association with specific features of the microstructure, such as regions of particular orientation. Further growth following nucleation may also be influenced by the orientation of adjacent regions. This results in a particular texture being developed in the recrystallized steel [15].

This concludes the review of the thermo-mechanical principles that govern the properties of continuous annealed steels. The remainder of this section goes on to look at modelling principles and their use in related fields. Initially this covers the methods used to vet the data in its received form.

2.5. Data Cleaning

Although many authors made reference to their attempts to 'clean' their data it was difficult to find relevant work on the subject. Often the impact of unclean data on results would be highlighted but rarely would details of the methods taken to remedy the problem be detailed. It proved difficult to find papers on the subject that were based on industrial processes similar to the ones under investigation in this project.

Following the removal of obvious faults; such as missing values, values of significantly greater magnitude than others and incorrect entries (e.g. text rather than numbers); it can then difficult to assess the validity of the remaining data. Work by Tenner [37] on the modelling of heat treated steels included a substantial section on data cleaning, as well a robust method for identifying data that needed investigation. This work proposed a structured procedure for detecting outlying data points and was also relevant due to its use of neural networks within the steel industry.

Finding other specific references to data cleaning was quite difficult. For example Jones[38] makes little reference to any data cleaning methods used in his work. Other work made reference to data cleaning taking place but gave no details of the methodology used. This same difficulty was found by Tenner.

2.5.1. Are Outlying Data Points All Faulty?

A first approach that one may take when dealing with problems similar to this is to assume that all outlying data points are faulty and therefore remove them. This was observed by both this author and by Tenner. Outlying data points are defined as those that are 'statistically different to the rest' [37] or those that carry 'a high statistical leverage' [39]. It is also important to define what is meant by a 'faulty' data point. In the work by Tenner this term referred to a measurement that had a deviation from the expected value which was greater than the measurement tolerance established for that point. As the data cleaning techniques used for this work followed on from Tenner's suggestions it was decided to utilise the same definition.

By investigating why these outliers occur one can then state whether they are indeed faulty, and so can be discarded, or if they are in fact valid and by removing them the integrity of the model is reduced.

2.5.2. Reasons for Outlying Data Points

Tenner points out several reasons for outlying data points to exist with relation to the heat treatment processes under investigation in his work. As pointed out in his work, many of these reasons hold true for the annealing process and for industrial processes in general. The main reasons are described below.

- Data handling errors: These often relate to the way that data is stored, sorted or retrieved. It is often the case that information for processes can be stored in more than one database, so errors may occur when all the data is compiled. There is also the possibility that the same data may be recorded several times. Though the data would not necessarily be faulty it may induce problems in later models as it does not fully reflect the true underlying processes. Another problem that may occur relates to the sorting of data by an index in order to merge variables. If this index becomes corrupt in some way then whole sets of data may become faulty.

- Measurement faults: The data used for this project is the result of several measurements taken throughout the process. Though many of the methods used are robust it is still possible that errors will occur. For example, measuring the composition of the steel requires specialist equipment that is regularly calibrated. Slight variations, or malfunctions in this equipment, will result in errors. Several temperature measurements are included within the modelling data. These are based on average readings taken within the furnaces and at the other processing stages. Large peaks and dips in the temperature for short amounts of time will not be recorded, but are likely to have a profound effect upon the steels properties.
- Process faults: The most important feature in this category is factors which vary from treatment to treatment but are not logged in the data set. The temperature example above may be considered an example of this. Even if these are monitored during the processing, and deemed to be acceptable at the time, a combination of these variations not being logged may generate faulty data points that do not relate to the recorded processing conditions.
- Typographical Errors: Human generated errors may be introduced if results are recorded manually or when data is transferred to a database via keyboard. In both cases faulty data would be generated. The magnitude of these errors is hard to quantify. Simple typing mistakes, i.e. recording temperature as 785 rather than 758, would not be so significant. In the cases of values less than one, or around this magnitude, missing out the decimal place would result in an error of several orders of magnitude.

- Incorrect treatment: Specific heat treatment cycles are applied to the different grades of steel while they are being annealed. This control allows for precipitates to form at the right times and stops phase changes from occurring. The treatment cycle needs to be matched to specific steel chemistries in order to obtain the desired properties. In some circumstances the chemistry and heat treatment may not match up, leading to outlying data points. These will still be of use when modelling provided the actual treatment and chemistry are logged. Another cause of faults in this category may be related to incorrect use of the plant. Temperatures may be lower than required in order to cut costs and speeds set might be slightly higher to meet quotas. Both these examples would again lead to faulty data points, but they would again be valid if the actual treatments are recorded.

2.5.3. Basic Outlier Detection Techniques

As a first approach to data cleaning a basic detection method should be employed. This involves looking at the range in which the input variables should lie and investigate points that fall outside of these limits. For example, the cold rolled reduction value must be positive, any negative values found can be removed. Another likely problem would be coils having excessively large values for some inputs; these too can be removed.

Similar outlier detection uses the available data to check its own integrity. The idea here is that in an industrial process like continuous annealing, the same type of steel may have been processed before under similar conditions. By finding coils within the data set with similar input conditions the resulting properties of these inputs can be compared.

2.5.4. Model Based Outlier Detection

There are also opportunities to look for faulty data points during model training and testing. These techniques have not yet been used for this work but they will be once sufficient progress has been made with modelling. Tenner points out that outlying data points generally lead to higher errors being recorded. Larger modelling errors may be due to two reasons. First, the modelling technique used is not capable of fitting the data. A common example of this would be using a technique that has fewer dimensions than the actual process. A residual will then be present, not necessarily because the data is wrong but because the modelling technique is not flexible enough. Even in a flexible modelling approach there will always be a level of residual error present due to noise in the data. This requires the model training method to take this into account so over fitting is prevented. The second reason is that data may not fit even if the model provides a good representation of the process. This would be due to either data being correct but statistically different from previous examples or that the data is faulty in some way.

Once a model has been completed the residual error can be used as a bias for data cleaning, providing that the model covers a diverse range of examples. If a faulty data point lies within a sparse area of the data set, there is a danger that the modelling technique will try to fit to this point. In order to avoid this, models need to be constructed several times with different groups of test and training data.

Model outputs found to have high residual errors can be investigated. Those that are found not to be faulty can be left within the data set. Points that are found to be faulty can be corrected if possible or removed. By recording which data points have been checked it is then possible to find areas of the data set which could be improved by further data acquisition. If a checked data point constantly produced a high residual error this would be an indication of the model not being able to fit this data point.

2.6. Modelling Philosophies

Mathematical models of thermo-mechanical processes and microstructure evolution have been in developed since the early nineteen eighties, starting with the work by Sellars and co-workers at Sheffield University (cited in Hodgson [40]). This type of work was generally overlooked until the nineties, when the use of such modelling techniques started to grow. The advent of modern computers and the increase in their processing power lead to more of this work using more complex non-linear methods to quantify these relationships [40]. The increase in such work has meant that the acceptance of such models has increased. This is turn has accelerated their use within the industry [41]. While the confidence in the techniques used has risen it is still important that people can see that a model is representative of the actual process. White box techniques, such as simple linear regression relationships, can easily be understood as they contain representations of the physical mechanisms involved. This allows the origins of their working to be traced back to the initial principles. Black box methods, like neural networks, are not so clear and so need to be made more transparent.

Many of the techniques used to model steel grades rely on fitting constants in equations to suit the specific type. The resulting models are therefore only applicable to that grade, or ones very similar. For some properties, fitting these coefficients can be time consuming; so much so that doing so may be beyond the time period of this project. However, there are clear patterns that can be observed in the behaviour of some of these properties, though they might not be quantifiable. For example, the toughness of steel may be increased by creating a more chaotic microstructure so that propagating cracks are deflected more often. Though this is a clear relationship, the extent that the toughness increases cannot be predicted [42].

What is needed is a method that can be used to recognise these patterns or work with qualitative information. Ideally, this solution would utilise data provided by the annealing process, as well as the steel chemistry and details of previous processing. These would then be used as the inputs to a model that would calculate the desired outputs. One difficulty that may arise using this solution is how adaptable the model would be, should it be used on different hardware or if the current processing route was upgraded.

Another important aspect that needs to be considered is the complexity of the situation. Some methods may include certain assumptions or use approximations to obtain the final results. Using such a method would reduce the integrity of the model and possibly simplify it to such an extent that it became unacceptable. Though the final method chosen may reduce the pure mathematical accuracy of the model it should still produce results that are comparable with those of the actual process.

Computational models may be classified as black, white or grey boxes. The colour refers to the transparency of the model's working. A black box model may be considered closed, that is, that no information about the structure of the model or the relevance of each parameter can be perceived from it. A white box model will be the opposite of this, allowing for information about the process to be obtained from it. As is often the case with many practical problems, a grey box model falls somewhere in between these two extremes.

A solution put forward by Thompson & Kramer [43] to try and make grey box models more translucent was adopted by Jones et al [44] when considering property prediction from the Port Talbot hot strip mill. Here a black box model using artificial neural networks was combined with physical equations that would be considered white box models. Utilising such a method had the following benefits:

- Acceptance of the model is increased, with the white box section allowing observers to understand how the final solution is produced.
- The black box section of the model allowed for fine tuning of the physical equations.
- The use of the physical equations meant that prior work did not become obsolete

2.7. Computational Approaches within the Steel Industry

A review was carried out to assess the different computational approaches used within the steel industry. A paper by Bhadeshia [42] detailed the use of neural networks in material sciences. This detailed the basic principles of these approaches and complications that may arise from their use. Overfitting was identified as a potential problem associated with neural networks, where the model fits the training data but not further data. It suggested that to overcome this data should be divided into training and test data, with the training data used to make the model and the test data used to validate this model. An overview of where neural networks are used within the discipline to predict properties is included. This includes: welding and the measurement of weld toughness, strength, cooling rates and cracking issues; supperalloys and the effect on overall strength; fatigue problems including the onset of fatigue and creep; and finally transformation such as the martensite start temperature, continuous cooling curves and austenite formation. A brief section covers the modelling of steel processing, with the main focus being on hot rolling. Here two examples of property prediction are given, one using chemical composition and rolling parameters as inputs and the other using microstructural parameters. Two other models are included; one focusing on the prediction of finishing temperatures and the other concerns the control of strip temperature on the run out table. Further examples of the use of neural networks by other researches were also found [45-48]; some of these are highlighted below.

Jones [38] investigated the final properties of hot rolled coil produced at Port Talbot using models based on artificial neural networks. This work detailed the evolution the model through three stages. This started with a black box model based on a feedforward multi-layer perceptron network. Further the developments were made, moving through to a grey box model, by applying metallurgical knowledge to the choice of model inputs. The final approach combined a white box physical equation with a black box neural network approximating the error of this equation. The final model was found to provide the best predictive accuracy. The modelling approach was described by the author as 'a predictive model without non-value adding processes', meaning that the model was produced using only the mill operating conditions with no further metallurgical testing being required.

Capdevila et al [49] applied a neural network approach to the prediction of the final mechanical properties of low carbon continuous annealed steel. This work focused on the yield strength, ultimate strength and elongation values. The model utilised twenty inputs covering the entirety of the strips production. The breakdown of these inputs was as follows: hot rolling, five inputs (finishing temperature, reduction ferrite region and austenite region), cooling rate and coiling temperature); chemistry, ten inputs (carbon, manganese, silicon, phosphorus, sulphur, aluminium, nitrogen, titanium, vanadium and niobium); annealing conditions, five inputs (cold reduction, heating rate, annealing temperature, isothermal hold time and cooling rate). The model was trained using the properties and process conditions found from a literature review rather than the researchers own laboratory testing or measurements from an actual mill. The models produced by this work were then used to identify which factors had the largest effect on the final properties. The amount of carbon in the strip was found to significantly affect all three properties under investigation. The amount of manganese and phosphorus was found to have an influence on the ultimate tensile strength and elongation but not the yield stress. The opposite was found to be true with micro alloying elements such as titanium and niobium. A predicted strengthening of the steel was observed for higher cooling rates after annealing. The model was also successful at analysing the combined effect of factors, such as the coiling temperature and carbon content, allowing improvements in the process to be identified.

Whilst neural network type approaches seemed to make up the majority of the computational methods used within the steel industry examples of other methods were found. A paper by Thomas et al [50] detailed a method of predicting the hardenability of heat treated steels using a data mining approach. This technique stores previous process history, along with the associated mechanical properties, in a database. When a new set of processing conditions is queried, the database is searched for previous cases that are as close as possible to the query case. A normal approach may take ten values, five which are slightly higher than the query case and five that are lower. The final properties for the query case are then estimated using the values associated with the matching cases from the database. Their approach was later developed into a computer program called SteCal. They listed the benefits as being:

- The approach can be used for a wide range of compositions. For the present work this may allow for several grades to be combined into one model.
- Only a small amount of data is required in the range of interest.
- The method is ready for use once the minimum amount of data has been obtained.
- The method can be easily updated and maintained.
- Confidence intervals can be calculated for each prediction.

The above section highlights that there are several possible approaches that could be taken to model the mechanical properties of continuous annealed steels based on the processing conditions. Of these the use of artificial neural networks appears to be the most prevalent. For the purpose of this work it was decided that the focus should be on the use of a generalised regression network, as this approach appeared promising and had not been attempted previously. The use of artificial neural networks or similar techniques to study this problem would, however, produce an interesting comparison.

2.8. Generalised Regression Networks

Generalised regression networks are classified as a form of artificial neural network and operate in a similar manner to the data mining method outlined above. The model is set up using the known input data along with the associated known outputs. These are stored within the network as evidence. When a new case is presented to the network it calculates the output value based on weighted averages of the values stored in the network. These weights are calculated based on the distance the newly entered values are from those already held within the network. Further details of the workings of the network are described below.

2.8.1. Conception

The concept of generalised regression networks was first envisaged by Specht in 1990 [51]. His initial work focused on Probabilistic Neural Networks and relied on weighted-neighbour techniques. These networks perform classification tasks. A later paper [52] written in 1991 took this initial approach further and outlined the generalised regression network.

These networks produced models based almost directly from training data, giving them that advantage over more traditional networks of having no true learning phase during their development, other than changing the way that data is stored within the network. Specht's approach was to implement a statistical approach into the form of a neural network. All networks consist of four layers. The main regression layer is often very large, but can be reduced in size, through a training regime, without sacrificing the network's performance. However, the simplest approach is to utilise the full set of training data to make up this layer.

2.8.2. Architecture of networks

An example of a typical generalised regression network can be seen in Figure 2.18.

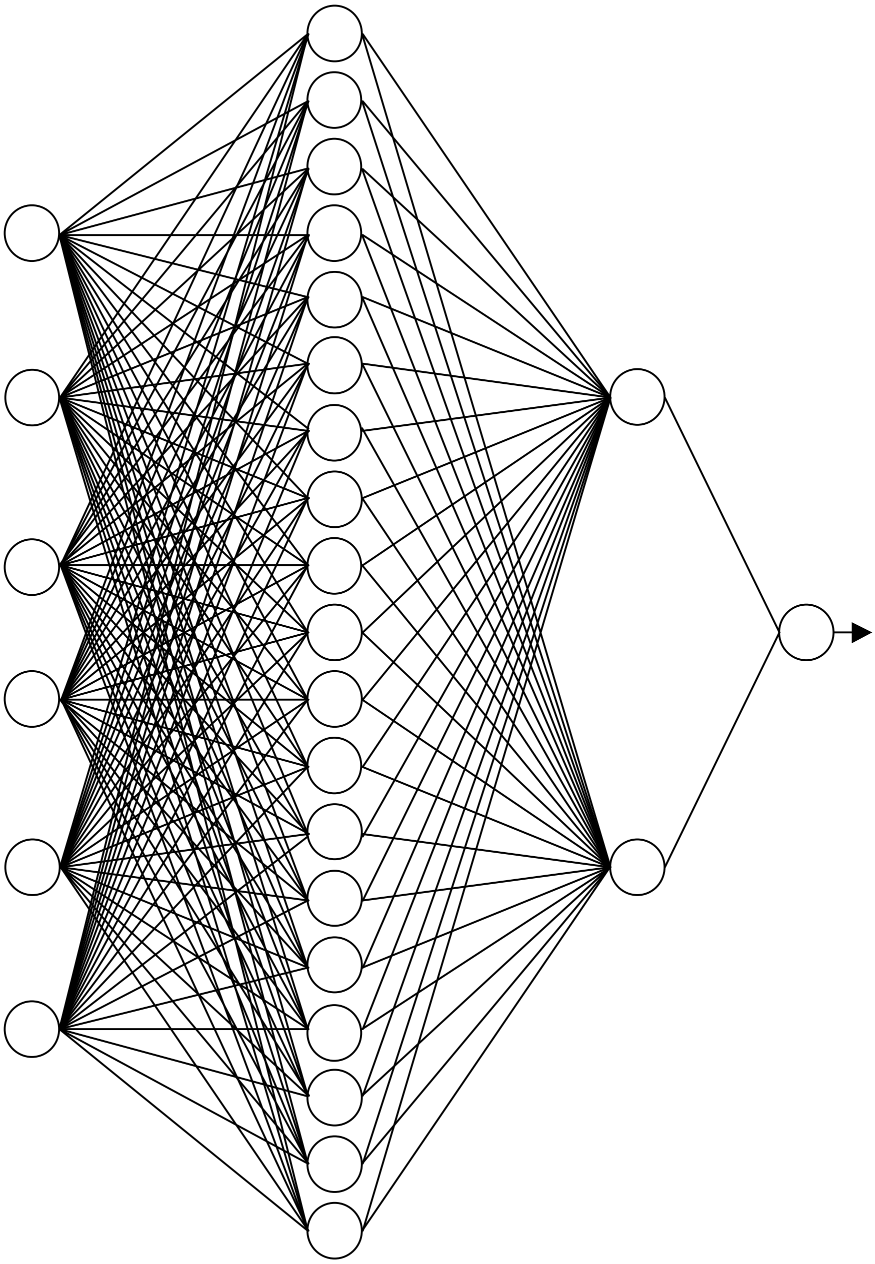


Figure 2.18: A typical generalised regression network with six predictors and twenty training cases

The first layer, called the input layer, has as many neurons as there are inputs (predictors) to the model. In order to gain optimum results from the network the range of the inputs should be standardized before being passed to the next layer.

The second, or hidden, layer has as many neurons as there are cases in the training data. Each neuron stores the values of the predictors for that case as well as the target values. Storing each training case can lead to the network becoming large and sometimes slow to compute. Values from the input layer pass to each of the neurons in the hidden layer which then go on to produce all outputs, though many of these will be zero. More details on the workings of the hidden layer are given later.

The next layer is called the summation layer and consists of two neurons. The one neuron is referred to as the denominator summation unit and the other the numerator summation unit. The denominator unit sums the weight values coming from the hidden layer, while the numerator unit finds the sum of these weights multiplied by the associated target values. The final decision layer divides the two values from the previous layer to give the predicted output.

2.8.3. Workings of the Hidden Layer

The first task of the hidden layer is to compute the distance between the newly entered data and values already stored in each of the network's neurons. A radial basis function is then applied to these distances to calculate the weight for each neuron. The radial basis function takes its name from the radial distance argument used. A larger distance value will mean that the weighted output is smaller, showing the current neuron has less influence than others. Figure 2.19 highlights this concept.

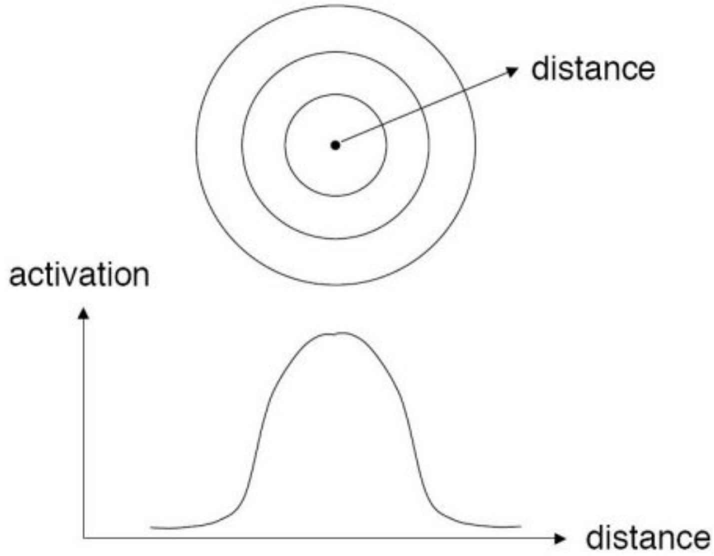


Figure 2.19: Illustration of a radial basis function

There are several types of radial basis functions that may be used, though typically a Gaussian function is used. If there is more than one predictor value, the radial basis function will have the same number of dimensions as there are variables, for example a two dimensional radial basis function is shown below in Figure 2.20.

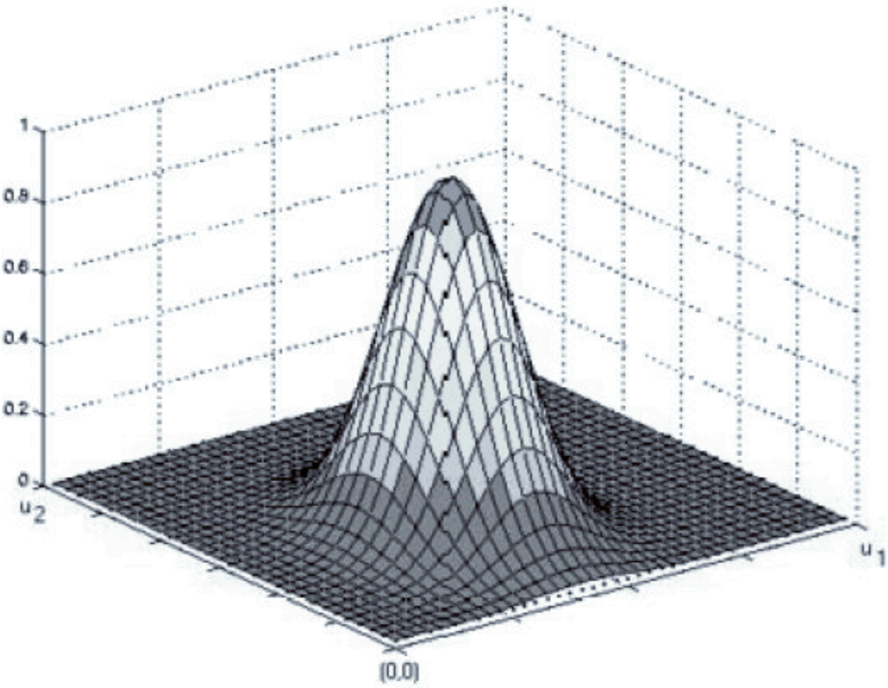


Figure 2.20: Multi-dimensional radial basis function

The peak value of the radial basis function is always at the centre, where the distance value is zero. This would result in the weighted output having matched the recorded value of the training data at that neuron. In order to tune the network there needs to be a way to alter the range of distances that the radial basis function at each neuron covers. This is governed by σ_s, which determines the spread of the function. How quickly the function declines as the distance increases is related to this, with larger values resulting in neurons at a greater distance having a greater influence. This is shown in Figure 2.21.

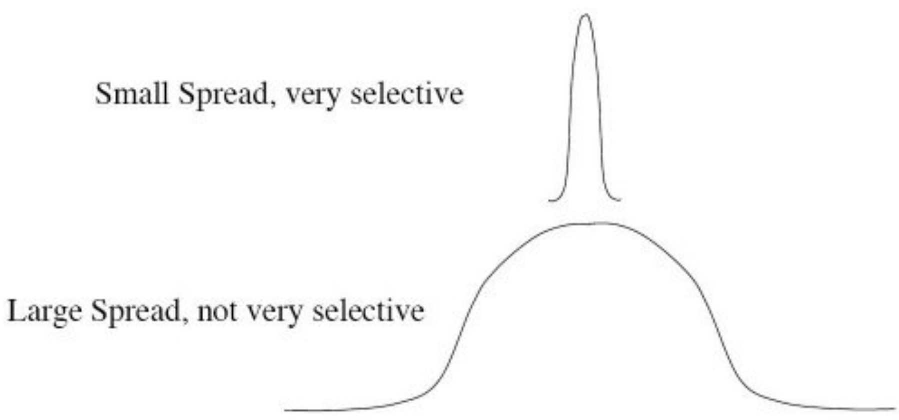


Figure 2.21: Radial basis functions with different spread (σ_s) values

The main aim when training a generalised regression network is to select an optimal spread value so that the spread of the radial basis function is controlled and only relevant neurons affect the model's output.

2.8.4. The Use of Generalised Regression Networks in Other Research

Generalised regression networks have been used in a wide variety of modelling situations, ranging from pharmaceutical work [53] and botany [54] to financial forecasting [55]. Much of the work found makes reference to more traditional neural networks and indicate that generalised regression networks are being used to obtain improved results. One benefit often cited is the lack of a true training stage.

In relation to material and metallurgical property prediction, two papers of interest were found. The first [56] of these concerned the ultimate tensile strength values of steel wires. The work relied on a network with only four inputs, including carbon content and the wire's dimensions. The results indicated that the model could accurately predict the ultimate tensile strength of the wires. The second [46] looked at the fracture toughness of micro-alloyed steels based on its processing conditions. This work paid particular attention to processes and additions used to control slag formation during secondary steel making that may have an impact on the steel's properties. Again a good correlation between predicted and actual results was reported.

2.9. Genetic Algorithms

Genetic algorithms offer an effective method of selecting the optimal input sets from the large list of possible combinations. They were first used by Holland in 1975 (cited in [57]). Though they are often thought of as an optimisation technique this is not strictly true. Though they may find a good solution to a problem it is very rarely the optimal one. However, in most engineering problems getting near to the optimal solution is normally sufficient [57].

Genetic algorithms mirror the process of natural selection by assessing the suitability of members of a population against a fitness function. A population member, or chromosome, is represented as a string of ones or zeroes. In this manner the algorithm can look at either integer values or a series of variables which are either on or off. Each member of the population represents a possible solution to the problem. Those members that meet the fitness function are kept and used to generate new populations, those that fail are rejected. A genetic algorithm may be represented using the schematic shown in Figure 2.22.

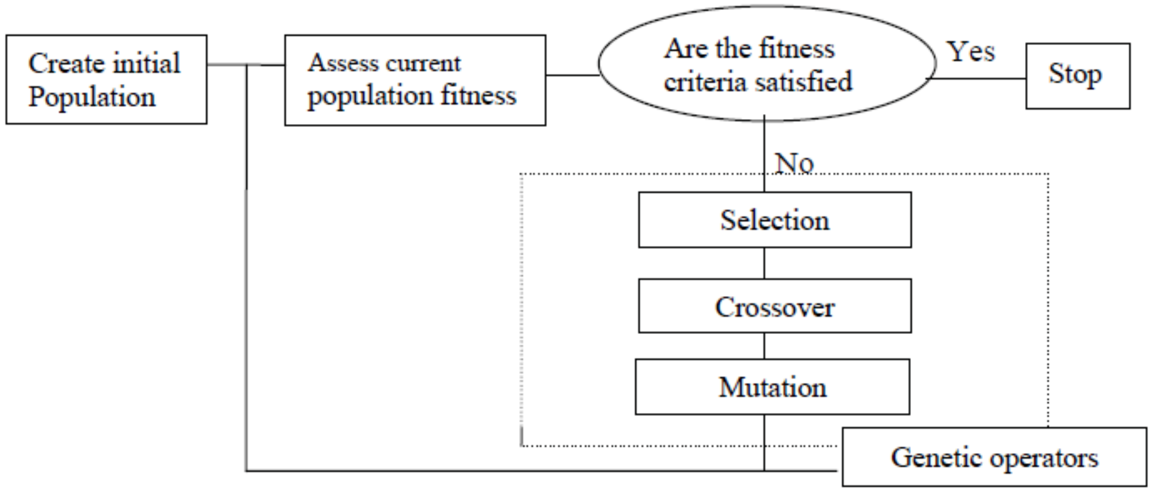


Figure 2.22 Schematic representation of a genetic algorithm [57]

The genetic operators, shown in Figure 2.22, are the essential parts of the algorithm. Once all the members of a population have been assessed against the fitness function they are then ranked in accordance with it. A certain proportion of these are then carried over, the selection phase, to undergo crossover. There are several methods that can be used to select the members which will be carried forward. The simplest of these is to take those members which best match the fitness function. Other methods include a tournament approach or roulette wheel system. In a tournament approach members are randomly paired up against each other. Those which best match the fitness function win and are carried over to the next round. With a roulette wheel system each member is designated a proportion of the wheel based on how well they match the fitness function. Numbers are then randomly rolled to select members from the wheel.

During the crossover phase the selected members of the population are merged with each other to form a new population. The selected members are paired together and then mated by means of choosing a random length at which to split them. This is shown in Figure 2.23.

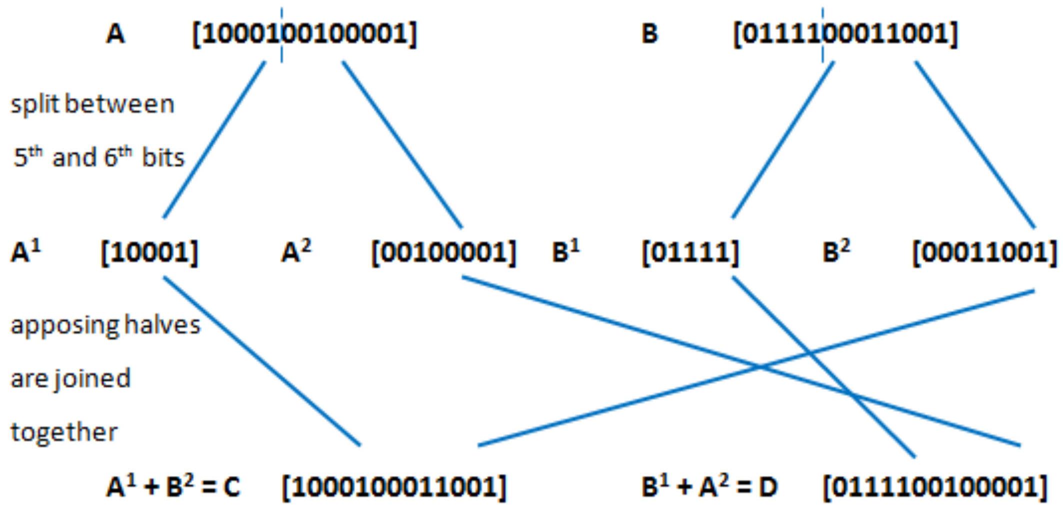


Figure 2.23: Mating process of a genetic algorithm

The mutation phase is present to stop the algorithm becoming trapped in a local minimum. In nature, mutations allow species to develop characteristics that are not present in the original population. Within a genetic algorithm, only a certain amount of information is available in a population. Crossover will try and find desirable solutions using this information alone. Mutations are beneficial as they introduce new data. This is particularly helpful if the original population is narrowly focused on one point in the solution set. Mutations can manifest themselves in a genetic algorithm by either inverting a random bit in a member, changing a zero to a one for example, or by modifying a series of bits.

2.10. Conclusions

Following a review of the available literature, a summary of the main conclusions are as follows:

- Strip steel is annealed to relieve stresses that have built up during previous processing, increasing its formability. Annealing requires the strip to be heated in a controlled manner to the required temperature, allowing this strip to soak at this temperature and finally cooling the strip.

- Continuous annealing allows this process to be carried out in about ten minutes, rather than the several days required to batch anneal coils. This increase in speed is due to strip being heated rapidly and higher temperatures than batch annealing being used.
- Continuous annealing is one of the final processes that strip steel undergoes before it is released to the customer. The annealing conditions and final properties are determined by the processing history, such as hot rolling conditions, casting chemistry and degree of cold reduction.
- Modelling the properties of continuous annealed steels requires an understanding of a variety of metallurgical principles. When considering the strength of these steels the grain size as well as the affect of chemical additions needs to be known. The formability of steels relates to the grain size and crystallographic texture of the steel. These complications in assessing the properties are currently overcome by means of a simple tensile test from which the appropriate mechanical properties can be determined.
- Other research has shown that the grain size can be related related to many of the processing conditions that the strip undergoes. Such factors include the annealing temperatures, soak times, amount of cold reduction and the influence of alloying additions
- Reliably predicting the mechanical properties of steel is an area that has been the focus of research for several years. Much of the early work in this area was overlooked until the advent of modern computing and the ability to implement more complex non-linear methods.
- Modelling techniques fall between two categorise; white box, where everything is known about the structure of the model (such as multiple-linear regression approach), and black box, where nothing is known about how the inputs create the outputs (such as a neural network). A grey-box approach describes anything in between these. Making a model

more transparent, moving it from black box to white box, is likely to increase confidence in the model and assist with its uptake.

- Artificial intelligence approaches have previously been used to model the properties of steel. The majority of these approaches rely on the use of artificial neural networks, though other approaches have also been considered. Generalised regression networks are a branch of artificial neural networks that has seen limited use within the steel industry; however other research areas suggest there are benefits to such an approach.
- A research opportunity exists to develop a method of predicting the mechanical properties of continuous annealed steels based on their processing conditions using an artificial intelligence type approach. Whilst the relationships governing these properties are based on metallurgical principles it may not be necessary to thoroughly understand them. Basing the model on actual process conditions means that the extra measurements required to quantify such relationships, such as grain size, are not required.

CHAPTER 3 – MULTIPLE LINEAR REGRESSION ANALYSIS OF THE CONTINUOUS ANNEALING PROCESS

3.1. Introduction

Regression analysis is a useful tool for the initial analysis of data. Unlike more advanced techniques, such as neural networks, training is not as time or data intensive. For this reason a model will be produced using regression analysis as comparative to the more advanced methods chosen. Regression analysis is the study of correlation through plotting correlated data [58]. In its simplest form a line of best fit can be used to describe a relationship. Typical this would be a straight line in the form $y = mx + c$. Correlation refers to when two quantities relate to each other, such that variation in one affects the variation in the other. *Positive correlation* describes when the variation is in the same direction; for example a perfect gas has a direct relationship between pressure and temperature, increasing the temperature causes the pressure to rise. The inverse of this is termed *negative correlation*. In this case variables move in the opposite direction, for example the unit price of an item will decrease if the volume ordered increases. Regression can take either a linear or non-linear form; the method of calculating the *'m'* and *'c'* values is dependent on the form of regression used and is given by specific formulae. These values are calculated by minimising the error between the line of best fit and the data points.

3.2. Linear Multiple Regression Analysis

The details of regression analysis given above apply to only single factors, i.e. one variable has an effect on one output. In the case of large scale industrial processes, such as continuous annealing, there will be more than one variable affecting each of the final properties. In order to model the annealing process a multiple regression approach must be employed. Linear multiple regression analysis takes the following form:

$$y = b_1x_1 + b_2x_2 + \ldots + b_nx_n + c \tag{3.1}$$

where *y* is the dependent variable (e.g. R_e, R_m, A etc...)

x_i is the independent variable (model inputs, e.g. percentage cold reduction, temperatures, etc...)

b_i is the regression coefficient (or slope) of the independent variable x_i

c is the intercept or constant

Each variable's regression coefficient (b_i) can be calculated by manipulation of the matrix form of the inputs. The following solution can be used:

$$b = (X'X)^{-1}X'Y \tag{3.2}$$

where X is the matrix of data for all the independent variables

X' is the transpose matrix of the independent variables X

Y is the vector of data for all dependent variables (Y is just one of the properties at any time)

This calculation can be carried out using the Matlab programming environment. A simple model can be created, with the majority of a data set used as the model training data and a smaller set used to validate the model. Because no actual training is needed, i.e. the model is created in a one hit approach with no optimisation required, a third data set is not required.

3.3 Non-linear Multiple Regression Analysis

In a linear regression system the increase in an independent variable is associated with a constant increase in the dependent variable. This represents an ideal scenario as these relationships are very easy to explain and quantify. In real world application more complex relationships are likely to exist. In these cases the change in the independent variable is no longer associated with a constant increase in the dependent variable; this is termed non-linear regression. A simple example of this is given by Miles & Shelvin [58], the effect of studying textbooks on a student's exam result. Whilst the first few textbooks will have a significant effect on the mark obtained the later books will produce a diminishing return. This relationship is shown in Figure 3.1.

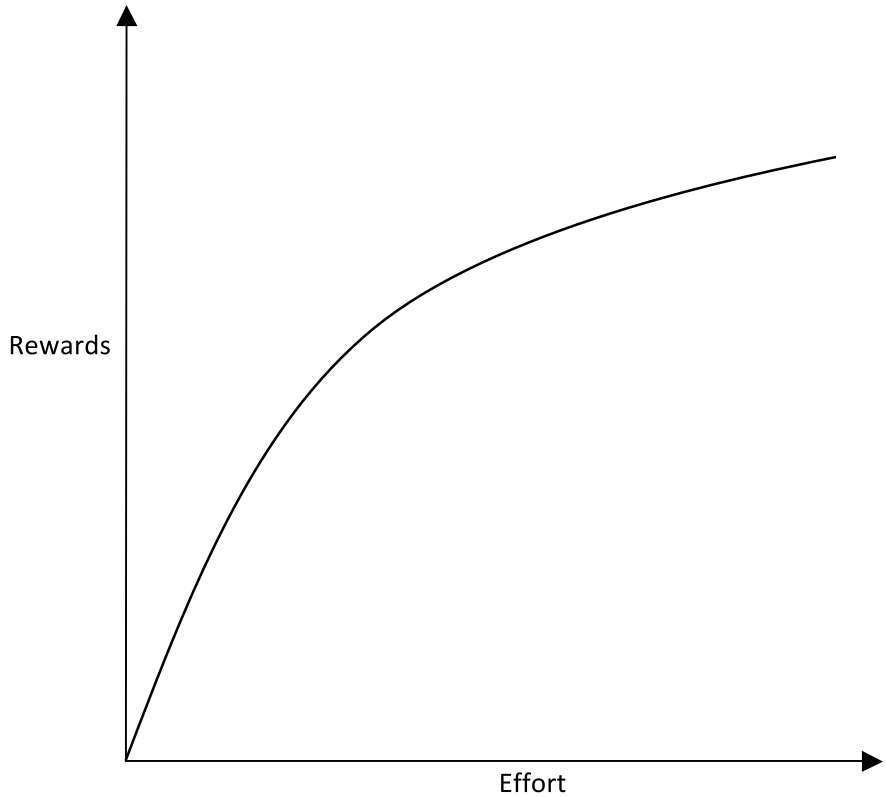


Figure 3.1: Curvilinear relationship between effort and rewards

When using non-linear multiple regression analysis several functions can be used to manipulate the input variables to achieve a suitable fit between the predicted output and the target value. These may include quadratic, cubic, log and inverse relationships. As an example a quadratic non-linear multiple regression equation is shown below.

$$y = b_1x_1 + b_2x_1^2 + b_3x_2 + b_4x_2^2 + \dots + c \quad (3.3)$$

The regression coefficient (b_i) for each variable can be calculated in a similar way to those in a multiple linear regression relationship through manipulation of the equation in its matrix form.

3.4 Initial Data for Regression Modelling

The continuous annealing process line at Port Talbot is capable of producing several types of steel. As previously stated, the initial aim of this project is to investigate only a few of these grades. It is envisaged that specific models for each of the grades will be produced rather than one generalised model of them all. The result of this should be an increase in the accuracy of the results at the expense of simplicity.

For the initial analysis only process data for the interstitial free steel grades, DC05 and DC06, produced at Port Talbot was used. A data set containing coils produced from the start of 2008 until week 12 of 2009 was used. The data set contained a total of 3706 entries. The data set was subjected to a cleaning regime similar to that detailed by Tenner [37]. Following cleaning the data set contained 3166 entries. Of these, 710 were split coils. A split coil refers to a coil which has been divided up after processing into two smaller coils to meet the needs of a customer. In these cases there is effectively a duplicate entry in the data set, as the processing conditions for each of these split coils are the same. For this reason it was decided to remove them from the data set as it was felt they may introduce bias and did not contain any additional information. With these entries removed a data set containing 2456 'clean' entries was produced. The data set contains coils regardless as to whether or not they met the required specification. Code was produced that allowed this to be taken into account. This allowed the following selections to be made: all coils, just those that met specification or those that failed to meet specification.

Initially each coil had 160 data entries. This was found to break down as 114 inputs and 46 outputs. The inputs included details that would be important to the model, i.e. chemistry, gauge, weight, annealing conditions etc, as well as data that would not be important, i.e. processing dates, customers, coil identification numbers etc. Following the removal of unnecessary data the number of inputs was reduced to 39, with the continuous annealing (CA) identification number being retained should later identification be needed.

Based on details in the literature it was decided that some additional variables needed to be calculated. The first of these was the percentage cold reduction. As there was no recorded value for this it was found using the hot rolled gauge and the final annealed gauge. This then replaced the hot rolled gauge in the list of possible inputs. Secondly, the titanium excess value was also calculated. This was found using the following equation:

$$Ti^* = Ti - 4C - 3.42N - 1.5S \tag{3.4}$$

Of the 46 outputs columns only five of them pertained to the properties that were under investigation in this project, the proof stress, ultimate tensile strength, elongation, strain ratio and strain hardening exponent. Table 3.1 shows the maximum, minimum, mean, standard deviation and units of the input values and output properties from the cleaned data set.

3.5 Data Normalisation and Comparison

If the inputs to a regression model are of a similar scale then their effect on the output properties can easily be compared to each other. In order to do this the data needs to be normalised. Normalising can be carried out in a number of different ways, however for the purpose of this work it meant standardising the inputs so that they had a mean of zero and standard deviation of one. This was done applying the following equation to each set of input conditions:

$$x_i^n = \frac{x_i - \bar{X}}{\sigma_X} \tag{3.5}$$

where X is one complete set of variables

x_i is the current variable in the data set

x_i^n is the normalised value of the current variable

$\bar{X}$ is the mean of the set of variables X

σ_X is the standard deviation of the set of variable X

Table 3.1: DC05/06 cleaned data set input conditions and output properties

Quantity	**Max**	**Min**	**Mean**	**Std**	**Unit**
CA Gauge	1.63	0.50	0.93	0.33	(mm)
CA Width	1653	851	1192	212	(mm)
CA Weight	26.78	6.09	15.46	4.51	(tonnes)
Radiant Tube Furnace (RTF) (average)	806.44	668.45	739.74	21.62	(^{o}C)
Soak (average)	785.71	667.43	742.17	15.59	(^{o}C)
Controlled Gas Jet Cooling (CGJC) (average)	681.10	606.74	660.09	7.11	(^{o}C)
High Gas Jet Cooling (HGJC) (average)	465.21	284.21	382.86	45.79	(^{o}C)
Reheat Overage (ROA) (average)	476.11	307.52	402.86	30.85	(^{o}C)
Overage (average)	354.84	200.00	249.87	41.28	(^{o}C)
2nd Cooling (average)	249.28	175.26	210.38	8.39	(^{o}C)
HGJC Rate	101.0	16.1	54.7	11.2	(^{o}C/s)
Soak Time	254.0	40.0	63.7	20.9	(s)
Furnace Tension	10.20	2.70	4.76	2.05	(kN)
Temper Mill Tension In (TMTI)	90.90	20.60	41.67	12.53	(kN)
Temper Mill Tension Exit (TMTE)	90.20	13.90	41.42	12.44	(kN)
Temper Mill Load (TML)	989.00	4.70	310.64	207.41	(tonnes)
Temper Mill Speed (TMS)	440.20	96.10	299.80	74.73	(m/min)
Temper Mill Extension (TME)	1.372	0.068	0.728	0.182	(%)
Cold Reduction	0.961	0.111	0.728	0.101	(%)
Hot Rolled Drop Temperature	1273	1106	1208	23	(^{o}C)
Hot Rolled Coil Temperature	760	457	703	39	(^{o}C)
Hot Rolled Finishing Temperature	938	825	905	16	(^{o}C)
Hot Rolled Stand 5 Temperature (HRS5)	1148	959	1089	22	(^{o}C)
Carbon (C)	0.1750	0.0012	0.0042	0.0130	(%wt)
Silicon (Si)	0.2990	0.0010	0.0045	0.0126	(%wt)
Sulphur (S)	0.0290	0.0035	0.0113	0.0022	(%wt)
Phosphorus (P)	0.0630	0.0040	0.0101	0.0034	(%wt)
Manganese (Mn)	1.4810	0.0660	0.1351	0.1083	(%wt)
Nickel (Ni)	0.0410	0.0100	0.0158	0.0032	(%wt)
Copper (Cu)	0.0560	0.0090	0.0223	0.0069	(%wt)
Tin (Sn)	0.0200	0.0020	0.0080	0.0032	(%wt)
Vanadium (V)	0.0050	0.0010	0.0025	0.0008	(%wt)
Nitrogen (N)	0.0128	0.0014	0.0031	0.0006	(%wt)
Aluminium (Al) (total)	0.2420	0.0210	0.0504	0.0087	(%wt)
Aluminium (Al) (soluble)	0.2250	0.0200	0.0468	0.0080	(%wt)
Niobium (Nb)	0.0400	0.0010	0.0012	0.0026	(%wt)
Boron (B)	0.0031	0.0001	0.0001	0.0002	(%wt)
Titanium (Ti)	0.0770	0.0010	0.0539	0.0111	(%wt)
Chromium (Cr)	0.0480	0.0110	0.0192	0.0046	(%wt)
Titanium Excess (Ti*)	0.0387	-0.7469	0.0095	0.0607	
Ultimate Tensile Strength (Rm)	389.2	281.2	313.2	12.9	(N/mm^2)
Proof Stress (Re)	300.2	134.4	180.1	26.9	(N/mm^2)
Elongation (A)	51.73	32.38	42.44	2.26	(%)
Strain Ratio (r)	3.010	1.196	2.120	0.188	
Strain Hardening Exponent (n)	0.274	0.186	0.224	0.010	

A simple routine was written to carry out this process in Matlab. The means and standard deviation were recorded so that any results could be easily converted back to their standard form when required. Normalised values for the output properties were not calculated.

With all the possible inputs to the model scaled so that they were comparable a basic regression model of the annealing process could be produced. The importance of each of the inputs to this model could then be assessed by comparing the size of the coefficients of the regression model. Larger coefficients would indicate inputs that had the greatest effect on the property under investigation. One possible problem with such a method is that this depends on the range of data within the data set. If there is a wide range of values for one variable it will be scaled smaller and the regression coefficient will be larger. Whilst producing a large regression model is one way of carrying out this assessment it may not be the most suitable method. For one it is likely to produce an overly large model, with many of the inputs likely to be superfluous. An alternative form of input analysis would be to calculate the correlation coefficients between the inputs and the output properties.

The correlation coefficient, or Pearson product-moment correlation coefficient, is found by dividing the covariance of two data sets by the product of the two data sets' standard deviations. The correlation between the two data sets X (possible input) and Y (mechanical property) is denoted by the term r_{XY} [58]. The correlation coefficient for two data sets may be found using the following equation:

$$r_{XY}=\frac{Cov(X,Y)}{\sigma_X \sigma_Y}$$

$$r_{XY}=\frac{\sum_{i=1}^{n}(x_i-\overline{X})(y_i-\overline{Y})}{\sqrt{\sum_{i=1}^{n}(x_i-\overline{X})^2}\sqrt{\sum_{i=1}^{n}(y_i-\overline{Y})^2}} \tag{3.6}$$

where r_{XY} is the correlation coefficient of the sets of variables X and Y

X and is a complete set of variables

x_i is the current variables in the data sets

$\bar{X}$ is the mean of the set of variables X

σ_X is the standard deviation of the set of variable X

The Matlab programming environment used during this work already had a function that ran this calculation. This was run using the command *corrcoef*. Using this function the correlation coefficients between the process conditions and the mechanical properties of the interstitial free steels detailed above were found. These results are shown in Figures 3.2 to 3.6.

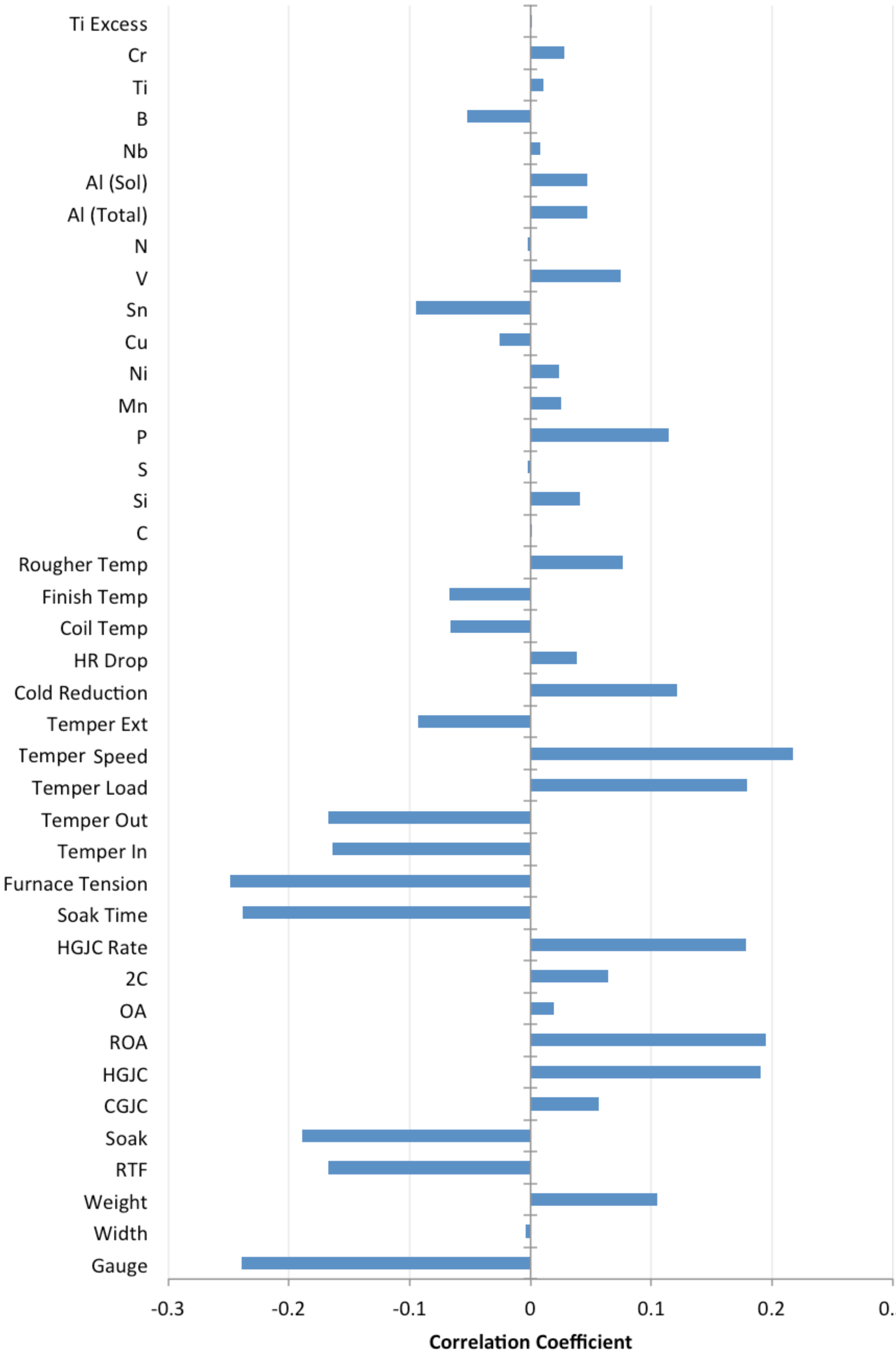


Figure 3.2: Correlations between ultimate tensile strength and process conditions of DC05/06 steel

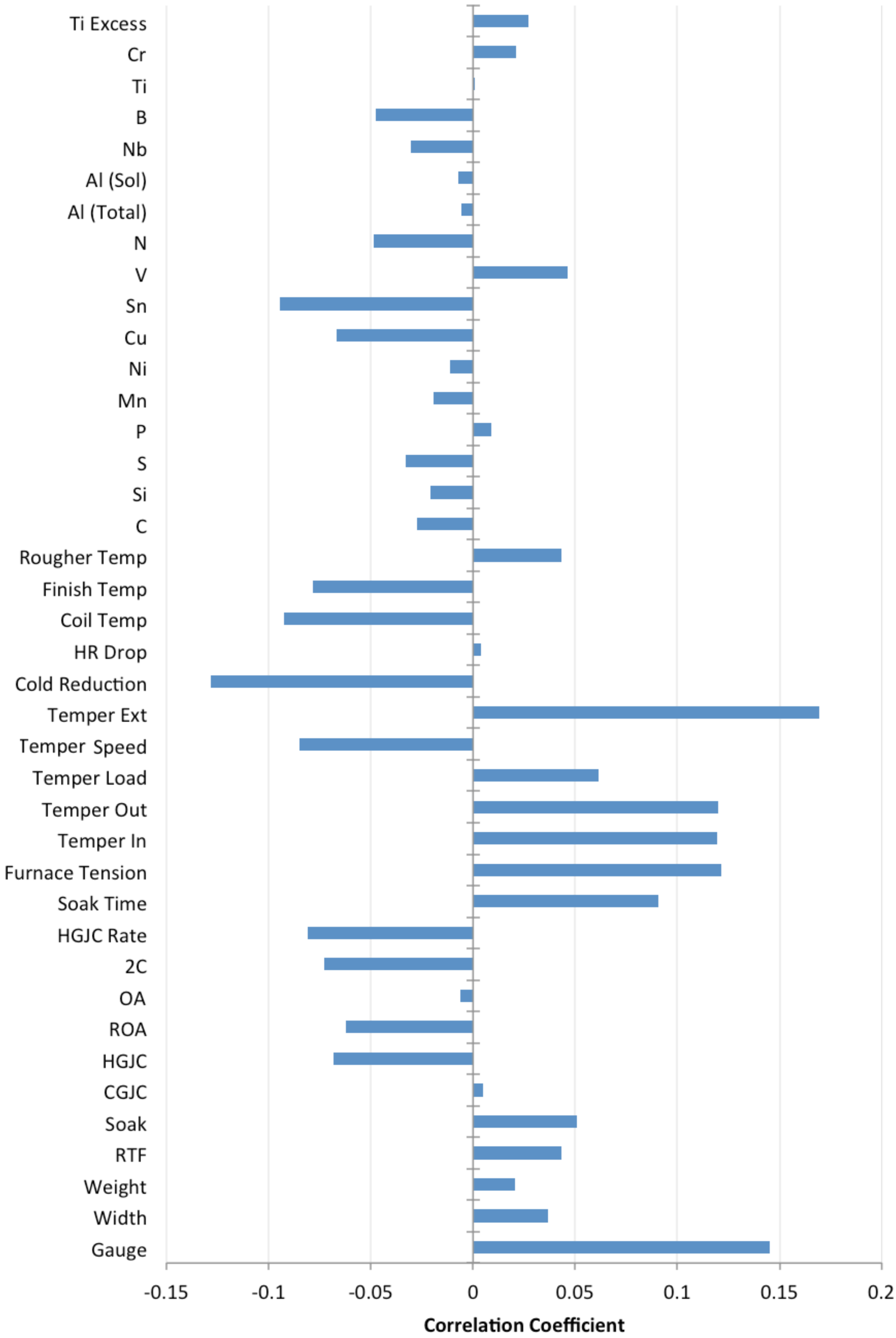


Figure 3.3: Correlations between proof stress and process conditions of DC05/06 steel

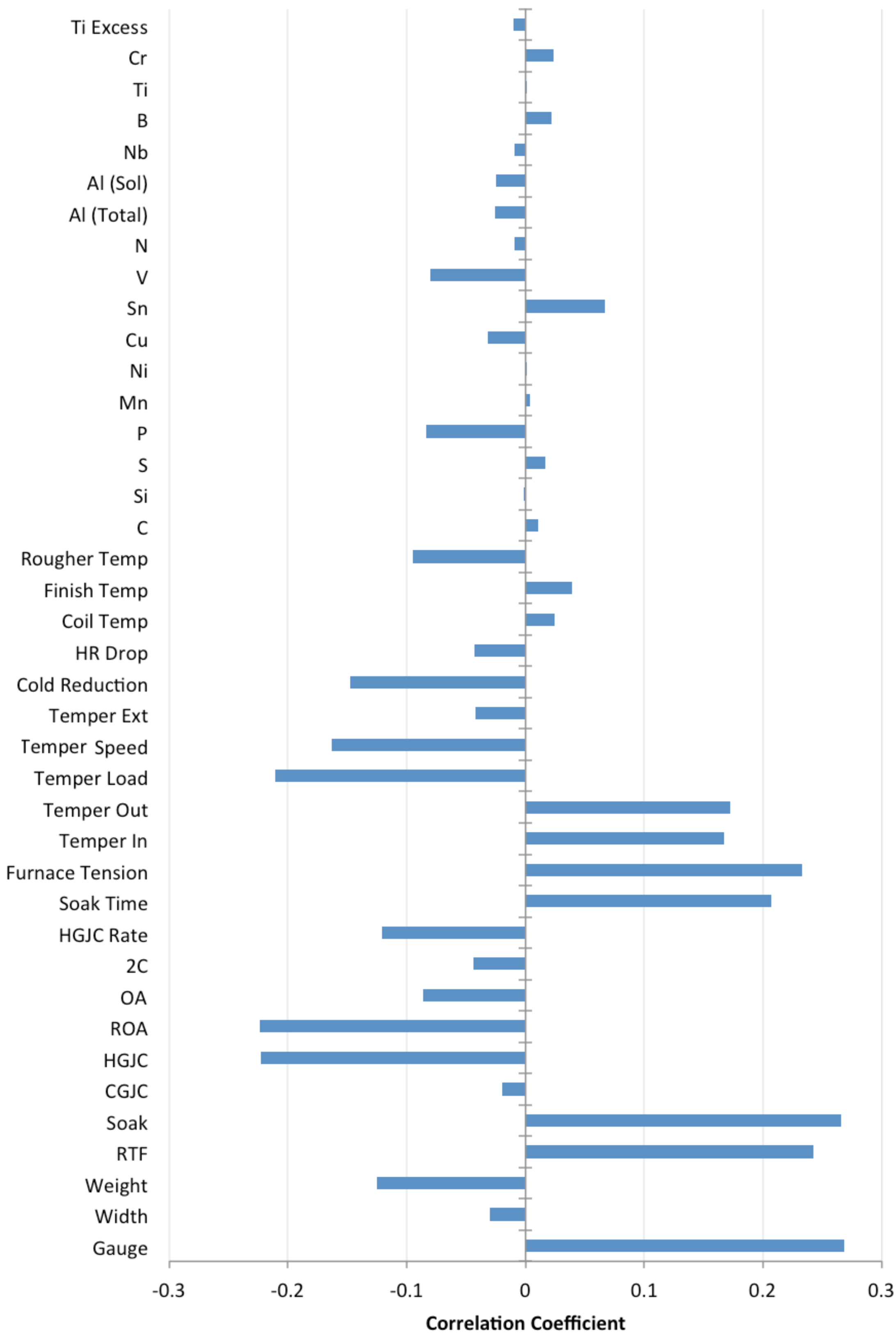


Figure 3.4: Correlations between elongation and process conditions of DC05/06 steel

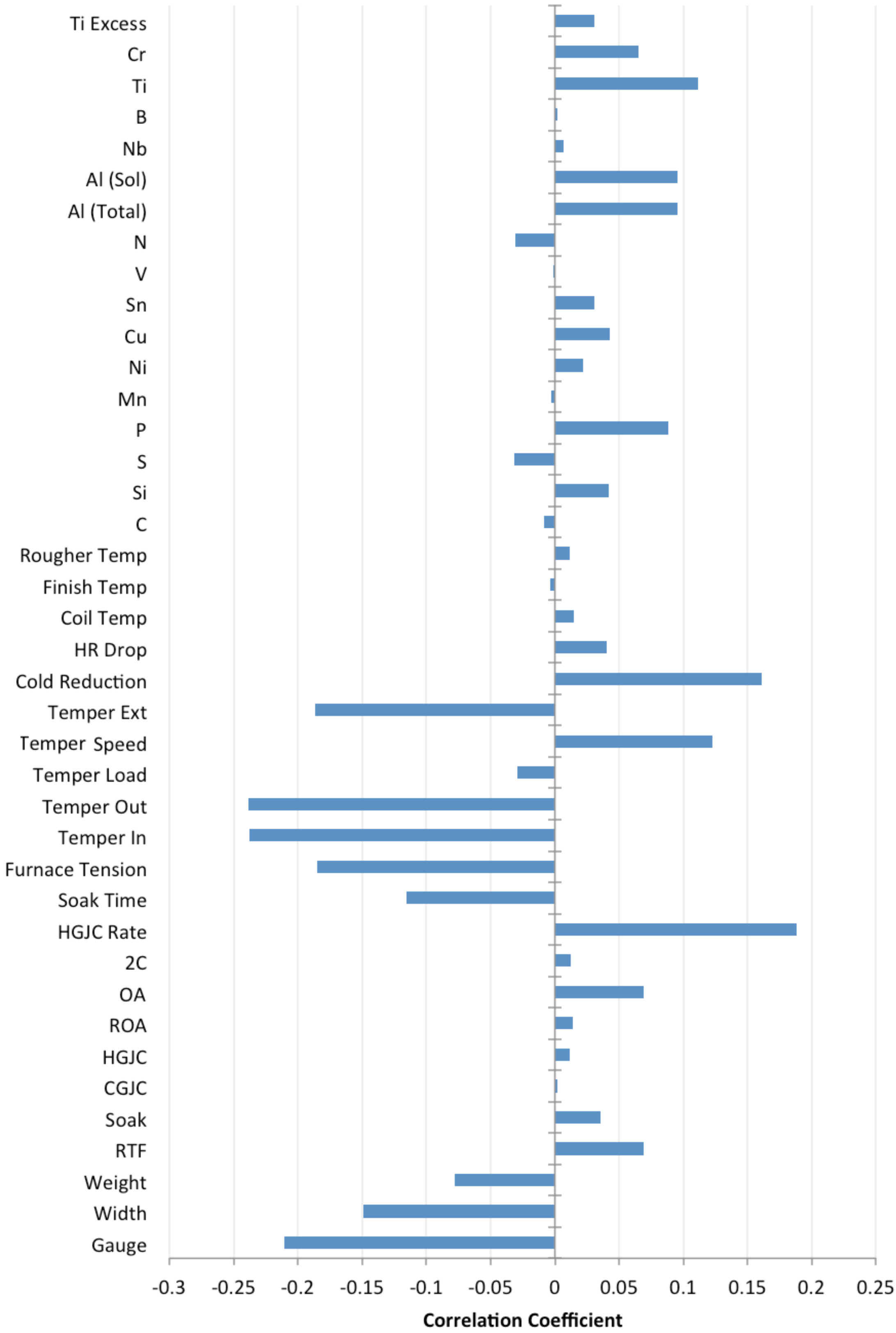


Figure 3.5: Correlations between r-value and process conditions of DC05/06 steel

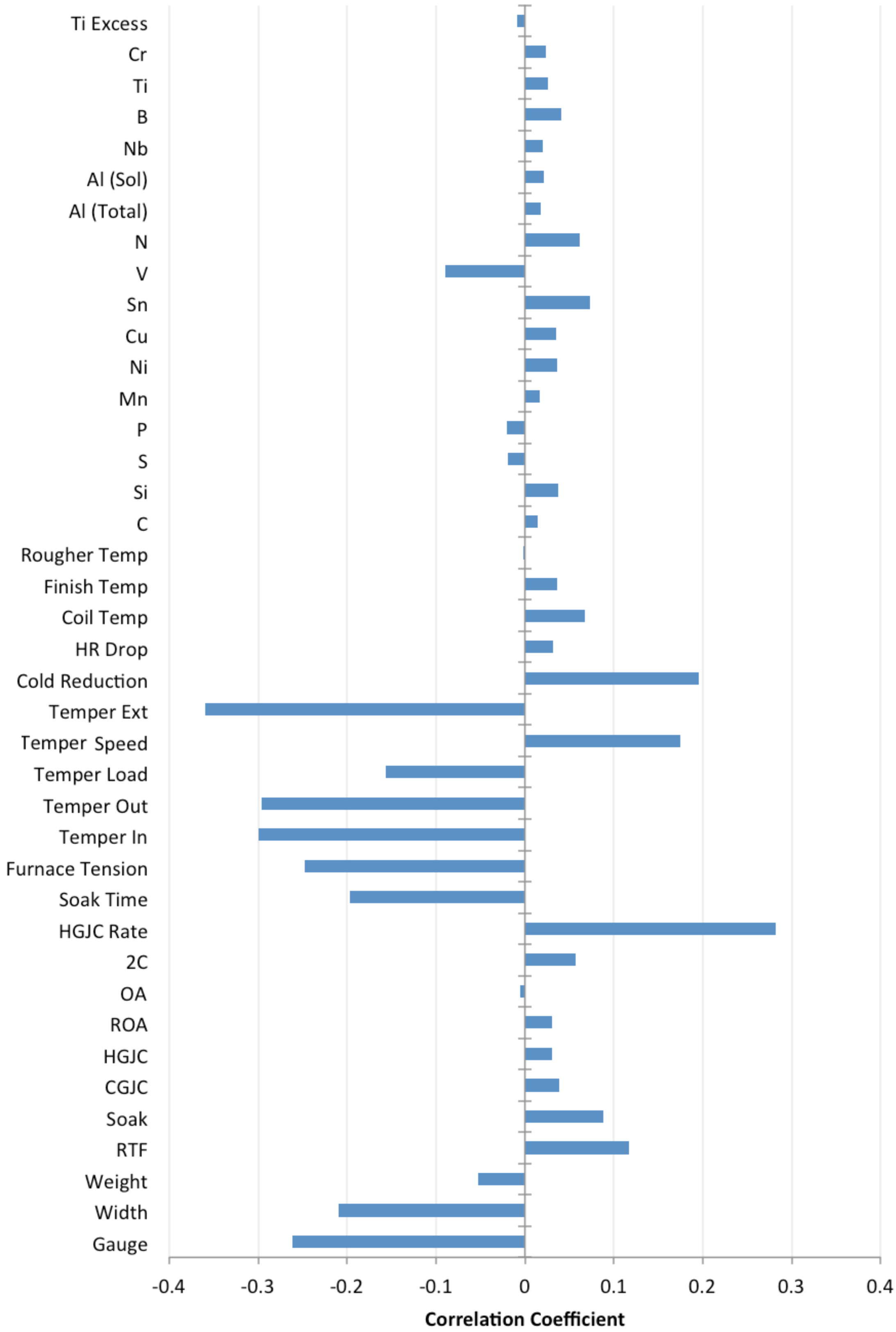


Figure 3.6: Correlations between n-value and process conditions of DC05/06 steel

From the correlation coefficient plots shown it is clear to see that there is a discrepancy between the relationships between the final properties and processing conditions (i.e. temperatures, loads applied, amount of reduction, etc...) and the steel chemistry. The results show that there are several weak linear relationships involving the process conditions but very few significant relationships attributed to the chemistry. This indicates that relationships involving the alloying additions added to the steel are complex and require more powerful methods to illustrate them. An alternative view may be that the steel chemistry is tightly controlled and so there is little chance of variation.

The physical dimensions, in particular the gauge, of the steel were found to have some of the strongest relationships with the properties. It seems strange that the gauge itself would have such a profound effect on the final properties of the steel; further interpretation reveals this may not be the case. Firstly one may consider the way that a strip heats up. The amount of heat that can propagate through the thickness of the steel is determined by several factors, in particular the gauge, heating time and temperature. This is governed by the heat transfer equation [59]:

$$\frac{dT}{dt} = \frac{k}{\rho C_p}\frac{\partial^2 T}{\partial x^2} \tag{3.7}$$

where T is the temperature

t is the time

k is the thermal conductivity

ρ is the density

C_p is the specific heat

x is the depth

In order that the required temperature propagates through the depth of a thicker coil a longer heating time is required, similarly thinner coils may be heated too much if the heating time is longer or the temperature higher. There are several stages during the annealing process alone where the temperature of the strip is critical. For example in order for recrystallization to occur a minimum temperature is required. Failing to reach this temperature would result in recrystallization not occurring and therefore the required formability would not be met. Heating a strip to too high a temperature may cause an issue during the soak stage. Due to the short time that a strip is held at temperature during this stage it can be heated above Ac_1, however if the temperature is too high, or carbon content is high, a phase change (from ferrite to austenite) may occur. This would alter the steel's microstructure and the desired properties would not be achieved [5].

The gauge also has an effect on the amount of cold reduction that can be applied to a coil. Due to the limits of the Port Talbot mills coils with a thicker finishing gauge cannot be subjected to as high a level of cold reduction as may be desirable. The cold reduction drives recrystallization by introducing stored energy into the steel by deforming structure. This is of particular importance when considering the strain ratio. Increased amounts of cold reduction have been shown to have positive influence on this property [32]. This relationship appears to be shown in Figure 3.5, where the correlation coefficient between the strain ratio and the gauge is approximately -0.21. This suggests that the r-value decreases as the gauge increases, or more likely that the level of cold reduction decreases as the gauge increases and so the strain ratio is lower.

3.6 Modelling Annealing Using a Regression Approach

A basic predictive model was created in the Matlab programming environment using the simple linear regression approach detailed above. In order to produce and train the model the available data set was split into two. The data set was sorted randomly when it was first imported into Matlab; this allowed the first 100 coils to be selected as validation data without there being any bias based on date processed, gauge or any other property that the data may have previously been sorted by. The validation data set was only shown to the regression model in order to produce predicted outputs, meaning it had no influence on the model's training. The remainder of the data set was used to train the model. All inputs were normalised before the model was trained. The output properties were left in their original form.

As a first approach individual models were made to predict the five properties under consideration using all forty available inputs. Plots of the predicted values obtained from these models against the actual recorded properties for the validation data set are shown in Figures 3.7 to 3.11. Lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results. Statistical data about all the models is shown in Table 3.2. The regression coefficients for the models are listed in Table 3.3.

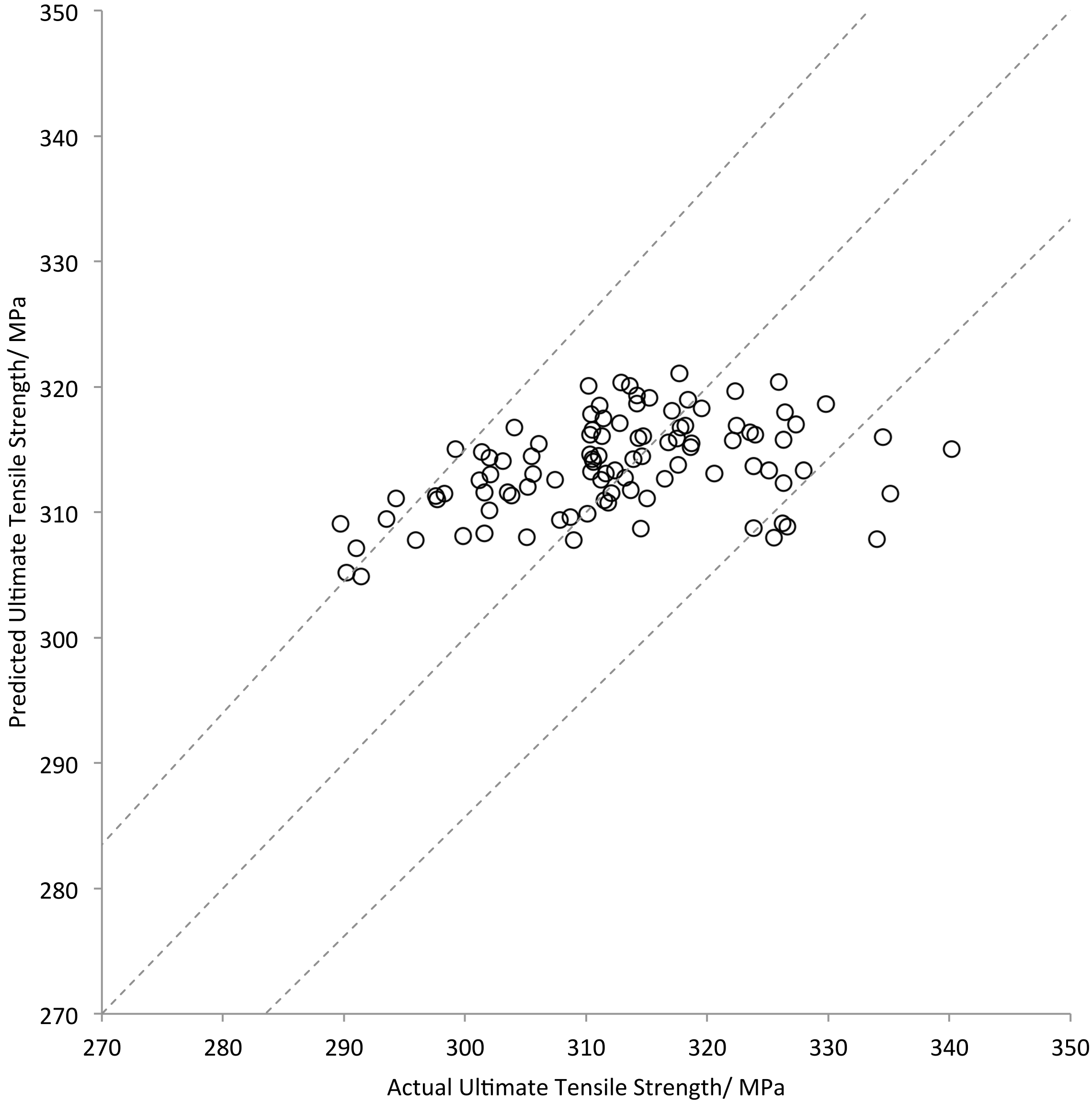


Figure 3.7: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a regression model for DC05/06 steels (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

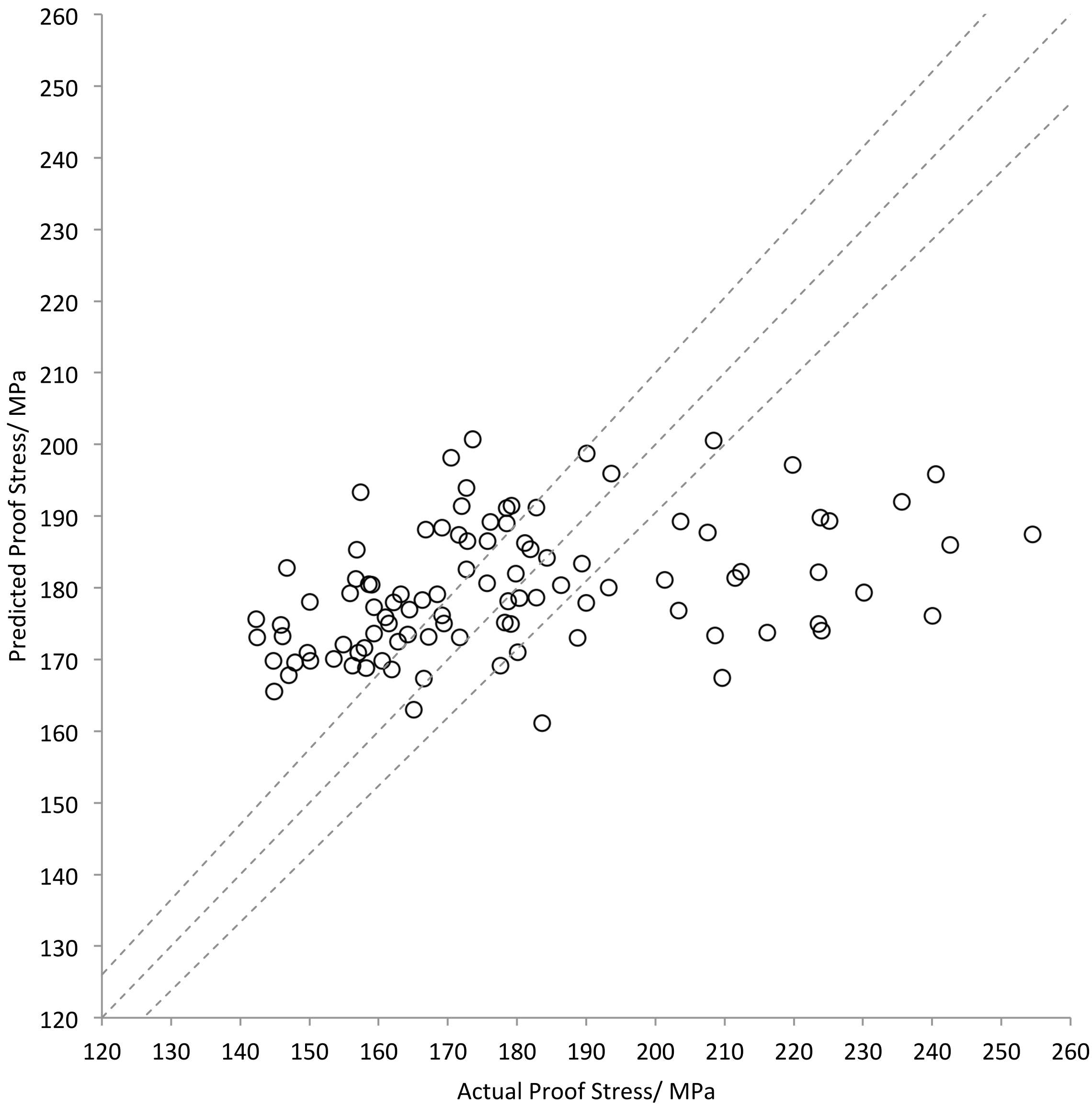


Figure 3.8: Actual proof stress values against proof stress values predicted by a regression model for DC05/06 steels (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

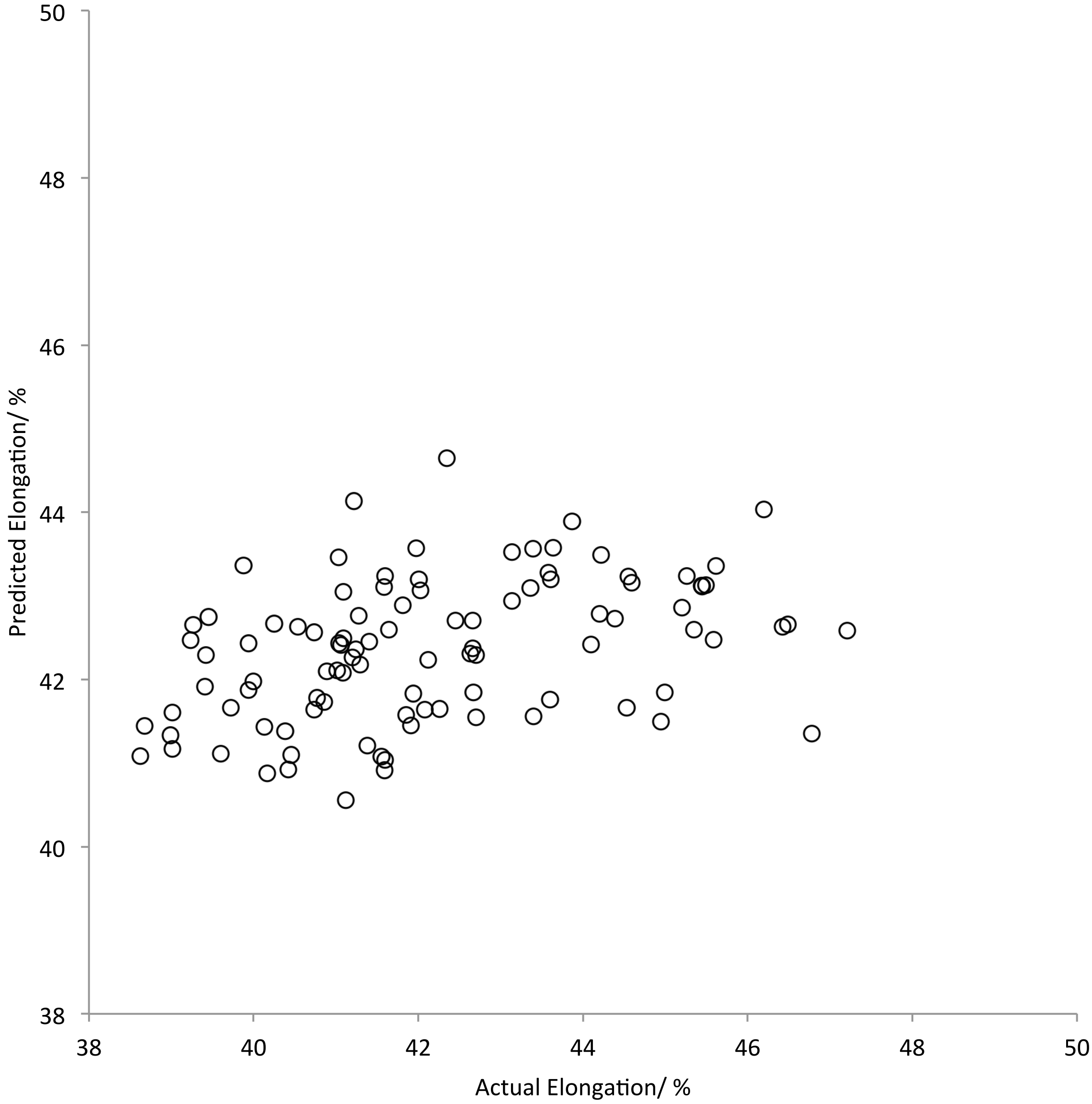


Figure 3.9: Actual elongation values against elongation values predicted by a regression model for DC05/06 steels (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

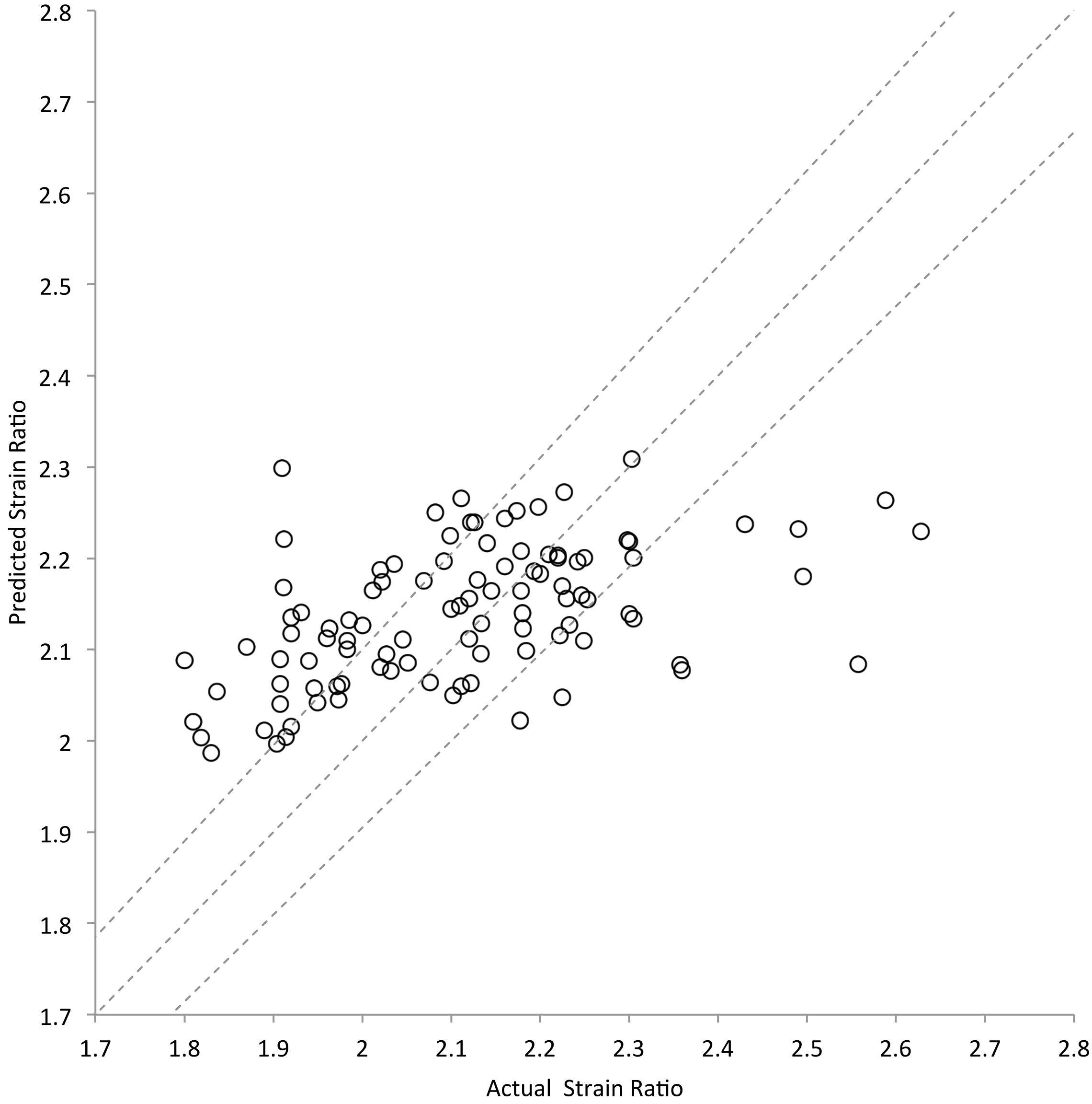


Figure 3.10: Actual strain ratio values against strain ratio values predicted by a regression model for DC05/06 steels (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

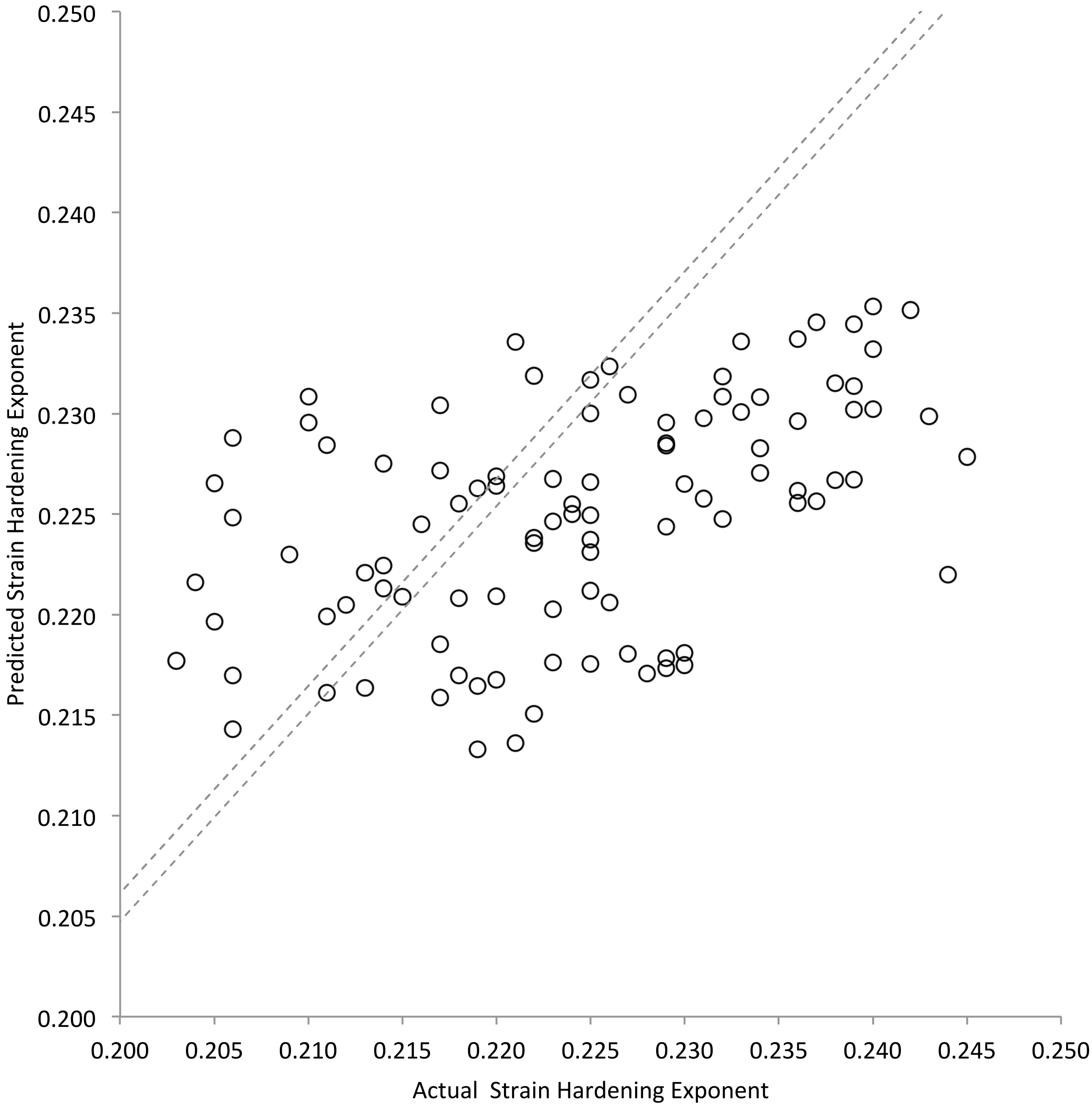


Figure 3.11: Actual strain hardening exponent values against strain hardening exponent values predicted by a regression model for DC05/06 steels (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

Table 3.2: Statistical data produced of validation data set from regression model of DC05/06 steels

Property	**MSE**	**RMSE**	**MPE**	**R**
Ultimate tensile strength	95.0	9.8	2.46%	0.39
Proof stress	584.0	24.2	10.62%	0.38
Elongation	3.987	2.00	3.85%	0.40
Strain ratio	0.024	0.15	5.84%	0.50
Strain hardening exponent	0.00010	0.010	3.47%	0.46

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Table 3.3: Regression model coefficients for DC05/06 steels

Input	**Rm**	**Re**	**A**	**r**	**n**
Intercept	313.2547	180.1261	42.4490	2.1214	0.2241
Gauge	3.1307	15.1021	0.9303	-0.0671	-0.0053
Width	0.2653	0.5247	-0.0108	0.0252	0.0002
Weight	0.4695	0.8216	-0.0390	-0.0093	0.0002
RTF temperature	0.3857	4.7193	0.2089	0.0099	0.0000
Soak temperature	-0.4850	-3.6533	0.1393	0.0220	0.0027
CGJC temperature	-0.4967	0.0501	0.0470	-0.0010	-0.0004
HGJC temperature	0.3593	-0.8486	-0.0784	-0.0058	0.0014
ROA temperature	1.0488	3.9389	0.0081	-0.0140	-0.0017
OA temperature	-0.5128	-0.7252	-0.0545	0.0181	0.0004
2C temperature	-0.2931	-1.7121	0.1372	0.0053	0.0011
HGJC rate	1.1668	3.6479	0.0392	-0.0092	0.0004
Soak time	-0.9330	-1.6630	0.2486	0.0408	0.0026
Furnace tension	-2.4100	-4.9217	-0.5447	0.0106	-0.0003
Temper mill tension in	14.8872	-3.7071	-3.6358	0.0082	-0.0165
Temper mill tension out	-15.4357	2.9984	3.7091	-0.0555	0.0161
Temper mill load	1.9917	4.8574	-0.0324	-0.0101	-0.0025
Temper mill speed	-0.1954	-2.0099	0.1899	0.0238	0.0016
Temper mill extension	-1.2077	1.1624	-0.2674	-0.0151	-0.0015
Cold reduction	-0.3472	-0.2286	0.0876	0.0032	-0.0001
Hot mill drop temperature	-0.1666	0.5373	0.0359	0.0077	0.0003
Hot mill coiling temperature	-0.4989	-1.3054	-0.0450	0.0034	0.0004
Hot mill finish temperature	-0.5731	-1.4205	0.1099	-0.0044	-0.0001
Hot mill rougher temperature	1.0694	2.0877	-0.1778	-0.0037	-0.0004
Carbon	-1.0778	-2.2084	0.0878	0.0303	0.0005
Silicon	-0.6908	-1.2257	0.1455	0.0043	0.0006
Sulphur	0.1857	-0.1116	0.0583	-0.0103	-0.0004
Phosphorus	1.7919	0.2996	-0.3288	0.0087	-0.0010
Manganese	2.9619	5.0019	-0.1473	-0.0294	-0.0007
Nickel	1.0149	0.8946	-0.0482	-0.0076	0.0000
Copper	-0.6760	-1.7546	-0.1217	0.0064	0.0002
Tin	-1.0353	-2.6432	0.0392	0.0110	0.0007
Vanadium	0.7310	1.7404	-0.1037	-0.0136	-0.0013
Nitrogen	-0.1643	-0.9609	-0.0497	-0.0114	0.0004
Aluminium (total)	4.7211	7.3979	-0.5732	0.0731	-0.0047
Aluminium (soluble)	-4.7930	-7.6751	0.5981	-0.0647	0.0049
Niobium	-1.2337	-2.6470	0.0336	0.0108	0.0004
Boron	-0.7306	-1.7005	0.0669	0.0155	0.0008
Titanium	-0.4841	-1.9624	0.1324	0.0472	0.0010
Chromium	-0.3860	0.7370	0.0896	0.0125	0.0001
Titanium excess	0.8327	1.5783	-0.0526	-0.0164	-0.0002

As shown by Figures 3.7 to 3.11 the simple regression approach using all the available model inputs was unable to produce reliable predictions of the properties of the mechanical properties of continuous annealed steels. Upon initial reviews Table 3.2 gives misleading results about the accuracy of these models. The small mean percentage errors may make the models appear to have a higher accuracy. These are in fact a product of the small range that the properties cover; for this reason the correlation value was used to show how the predictions related to the actual values.

One important observation is the disparity between the regression coefficients and the correlation coefficients, in particular the sign of some of the coefficients. It is important to note that there is a difference in what these values represent. The correlation coefficients represent the degree of fit between two variables, with their sign representing the slope of this agreement. In comparison the regression coefficients show the effect on the output value relating to a unit change in the associated function's inputs. These variances mean a direct comparison between the two values cannot be made and they should be used in conjunction with each other.

DC05 and DC06 steels are produced in a similar way, but the specification for DC06 is tighter than for DC05. A second set of regression models were made, this time only using coils whose properties had met the specification of the DC05 grade. This approach was taken to assess the influence that coils with outlying properties that had not met specification had on the overall data set. Upon removing the coils which had failed to meet specification the data set now contained 1277 coils. Models were made using the same approach as detailed above. These results are shown in Figures 3.12 to 3.16. Again, lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results. Statistical data about all the models is shown in table 3.4. The regression coefficients for the models are listed in Table 3.5.

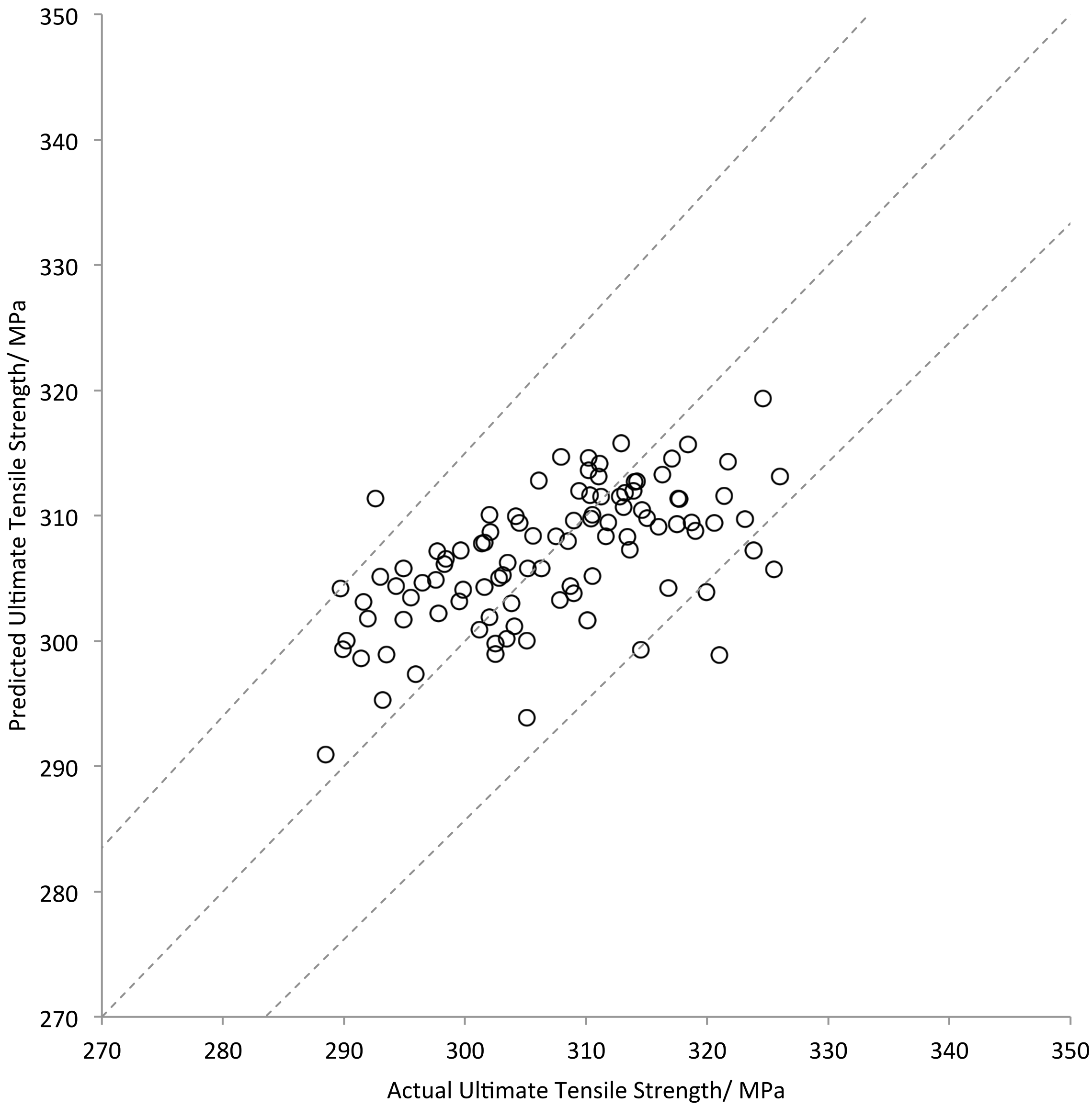


Figure 3.12: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

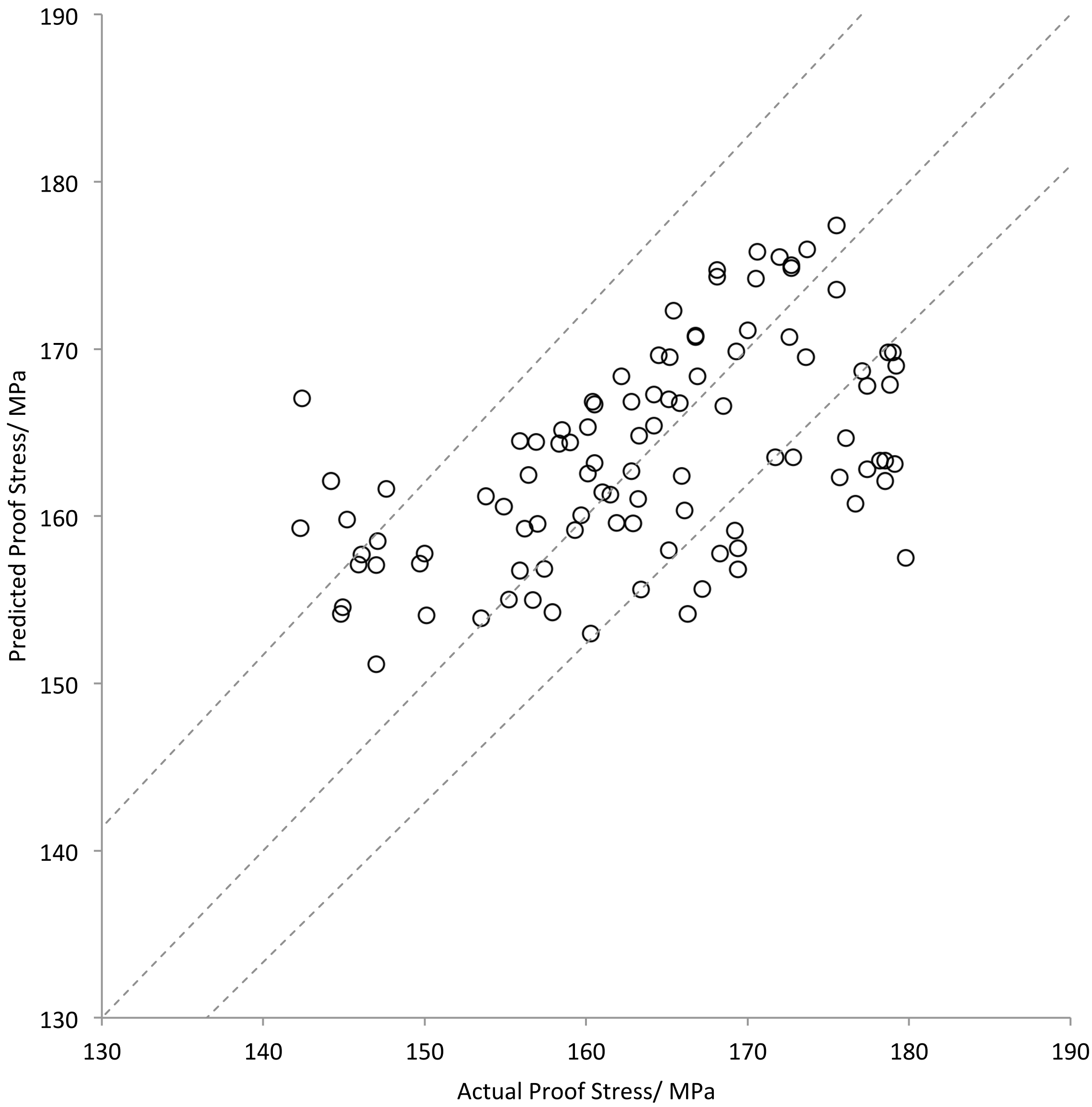


Figure 3.13: Actual proof stress values against proof stress values predicted by a regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

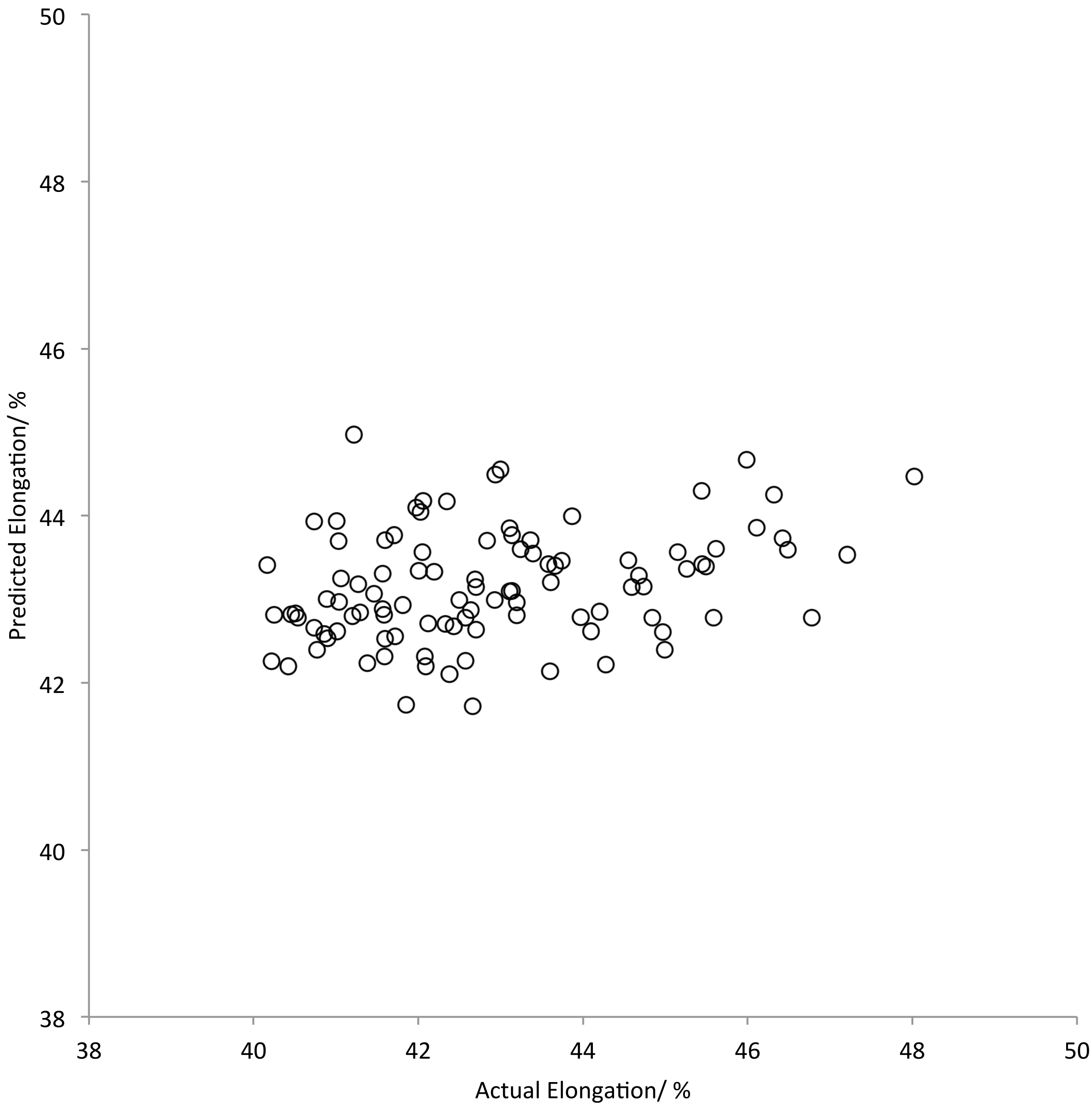


Figure 3.14: Actual elongation values against elongation values predicted by a regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

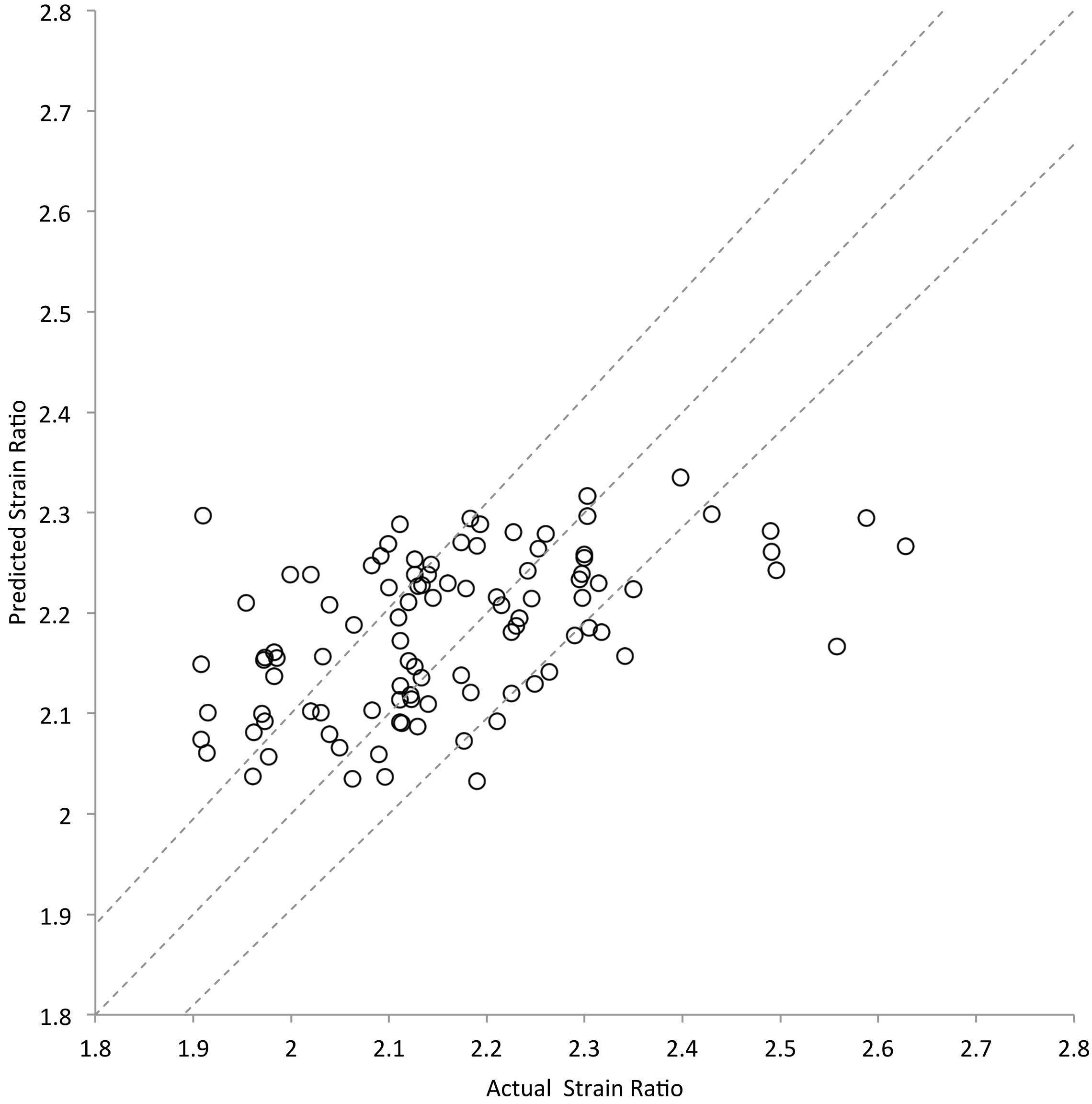


Figure 3.15: Actual strain ratio values against strain ratio values predicted by a regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

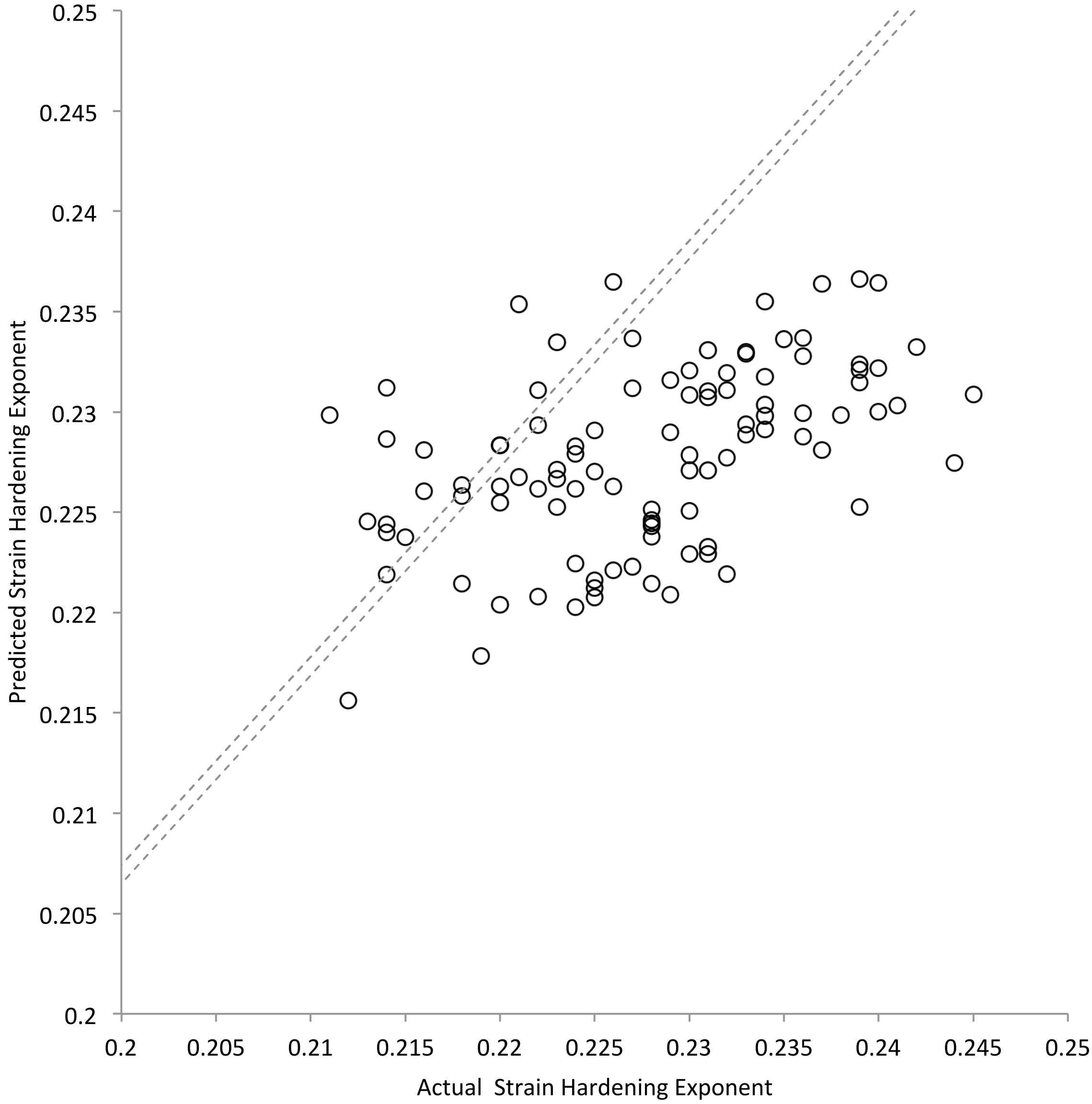


Figure 3.16: Actual strain hardening exponent values against strain hardening exponent values predicted by a regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

Table 3.4: Statistical data produced of validation data set from regression model of steels meeting DC05 specification

Property	**MSE**	**RMSE**	**MPE**	**R**
Ultimate tensile strength	57.9	7.6	1.96%	0.59
Proof stress	73.2	8.6	4.17%	0.53
Elongation	3.025	1.74	3.37%	0.30
Strain ratio	0.018	0.13	4.89%	0.49
Strain hardening exponent	0.00005	0.007	2.49%	0.48

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Table 3.5: Regression model coefficients for steels meeting DC05 specification

Input	Rm	Re	A	r	n
Intercept	307.2695	163.5093	43.0982	2.1765	0.2276
Gauge	-1.5716	3.0616	0.8279	-0.0485	-0.0033
Width	-0.6614	-3.1355	0.0170	0.0286	0.0009
Weight	0.3911	0.2567	-0.0389	-0.0154	0.0002
RTF temperature	-1.5231	-0.8911	0.1740	0.0371	0.0009
Soak temperature	1.0375	0.1963	-0.1288	-0.0220	0.0011
CGJC temperature	-0.5844	-0.3497	0.0190	0.0013	-0.0004
HGJC temperature	0.0342	0.3699	-0.2285	-0.0125	0.0010
ROA temperature	0.9199	0.5749	0.1623	-0.0101	-0.0011
OA temperature	0.4197	0.3783	-0.0210	0.0163	0.0003
2C temperature	0.4729	0.7504	0.0146	-0.0007	0.0003
HGJC rate	0.7007	0.6694	0.1115	-0.0108	0.0006
Soak time	-0.3547	-0.7254	0.0392	0.0268	0.0017
Furnace tension	0.8121	1.0991	-0.4775	-0.0079	-0.0011
Temper mill tension in	10.5201	5.3707	-1.9743	0.0679	-0.0119
Temper mill tension out	-10.5892	-2.8902	2.0617	-0.1063	0.0114
Temper mill load	1.7490	3.6561	-0.0916	-0.0076	-0.0017
Temper mill speed	0.6074	-1.9665	-0.0369	0.0227	0.0014
Temper mill extension	-1.6996	1.9383	0.1252	0.0026	-0.0002
Cold reduction	0.0149	-0.0767	0.0090	-0.0032	-0.0001
Hot mill drop temperature	-0.4030	-0.5716	0.0909	0.0111	0.0002
Hot mill coiling temperature	-0.2028	-0.4097	0.0388	0.0069	0.0004
Hot mill finish temperature	-0.2217	-0.4918	0.1078	-0.0003	0.0003
Hot mill rougher temperature	0.7454	0.7203	-0.1452	-0.0067	-0.0008
Carbon	0.0096	0.3034	0.1012	0.0293	0.0005
Silicon	-0.4945	-0.0261	0.0936	0.0004	0.0003
Sulphur	0.1929	-0.3717	0.1425	-0.0085	-0.0004
Phosphorus	1.7239	1.2006	-0.2049	0.0136	-0.0002
Manganese	1.7972	0.6219	-0.3659	-0.0327	-0.0011
Nickel	0.4996	0.3089	-0.0554	-0.0056	0.0005
Copper	-0.1413	0.4336	-0.0951	0.0051	-0.0002
Tin	-0.5028	-0.3001	-0.0239	0.0056	0.0003
Vanadium	0.6936	1.2773	-0.0343	-0.0120	-0.0014
Nitrogen	-0.1649	-0.0750	-0.0408	-0.0084	0.0002
Aluminium (total)	2.5112	2.5738	0.9371	0.1177	0.0006
Aluminium (soluble)	-2.2475	-2.4740	-0.9483	-0.1114	-0.0007
Niobium	-0.7691	-0.9754	0.1852	0.0068	0.0004
Boron	0.0952	-0.0929	0.0928	0.0133	0.0002
Titanium	0.8776	0.2652	0.1387	0.0398	0.0008
Chromium	-0.4372	0.2181	0.0345	0.0045	0.0001
Titanium excess	0.1417	-0.1925	-0.0686	-0.0174	-0.0003

Removing coils that failed to meet the DC05 specification significantly reduced the range over which predictions of the proof stress had to be made. A slight change in the range of ultimate tensile strength values was also observed. The range of values covered by the elongation, strain ratio and strain hardening exponent did not significantly alter. A difference in the results from each the models was observed as coils were removed from the data set if one or more of the properties fell out of specification, changing the available data for each model. Assuming that the models produce predictions similar to those using the previous model, an almost central value across the range, reducing this range alone will produce a lower mean error as the extreme values will be closer to this central one.

A final set of regression models was produced. The same data set was used to produce these models as was used to make the previous model. In order to analyse the effects of reducing the complexity of the model this set of models used a reduced number of inputs. The correlation coefficients between the output properties and the inputs were calculated. Based on these results it was decided that any input that had an absolute correlation coefficient value of 0.1 or above was used to make the model for that specific property. These results are shown in Figures 3.17 to 3.21. Again, lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results. Statistical data about all the models is shown in Table 3.6. The regression coefficients for the models are listed in Table 3.7.

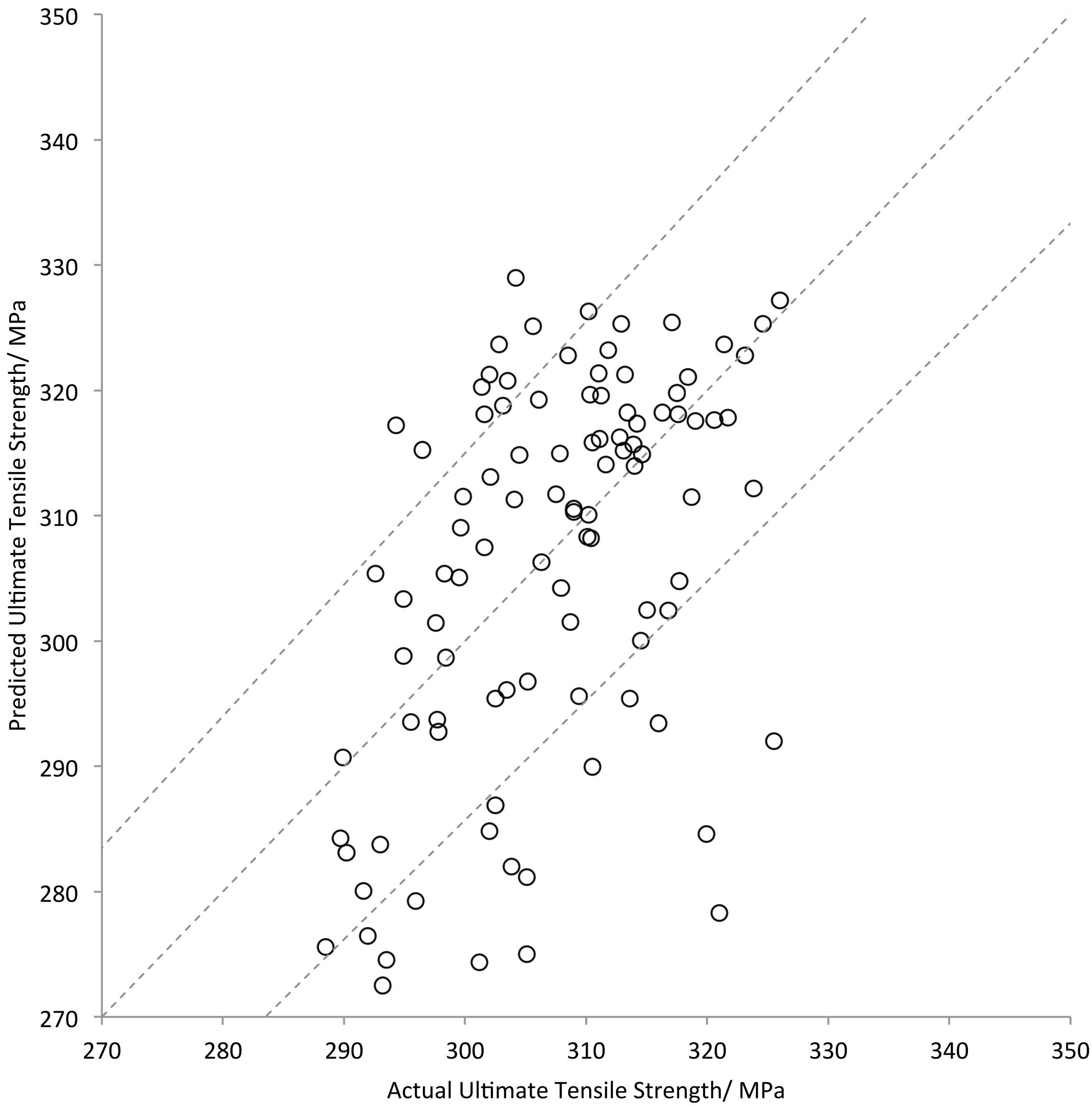


Figure 3.17: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

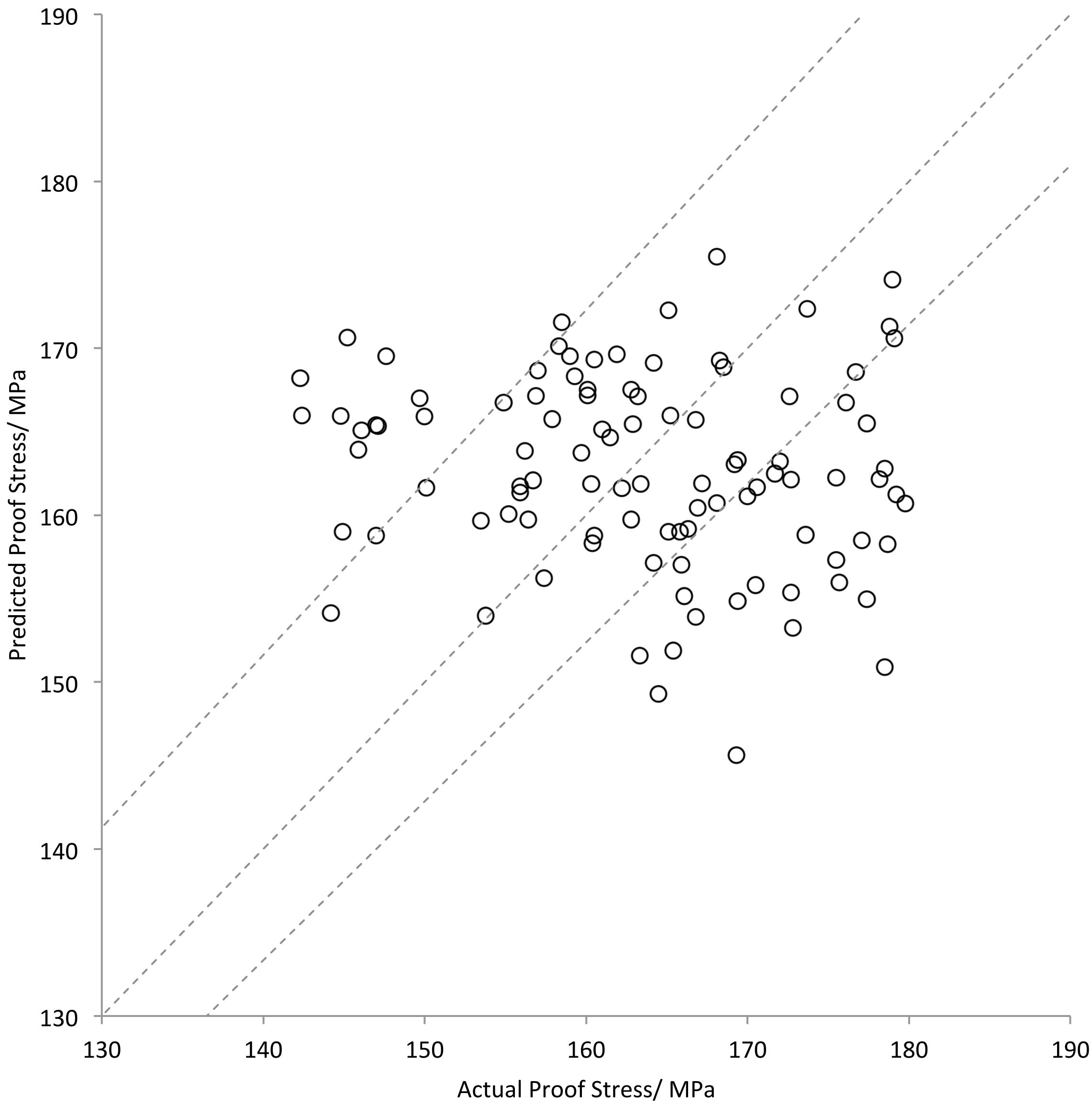


Figure 3.18: Actual proof stress values against proof stress values predicted by a regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

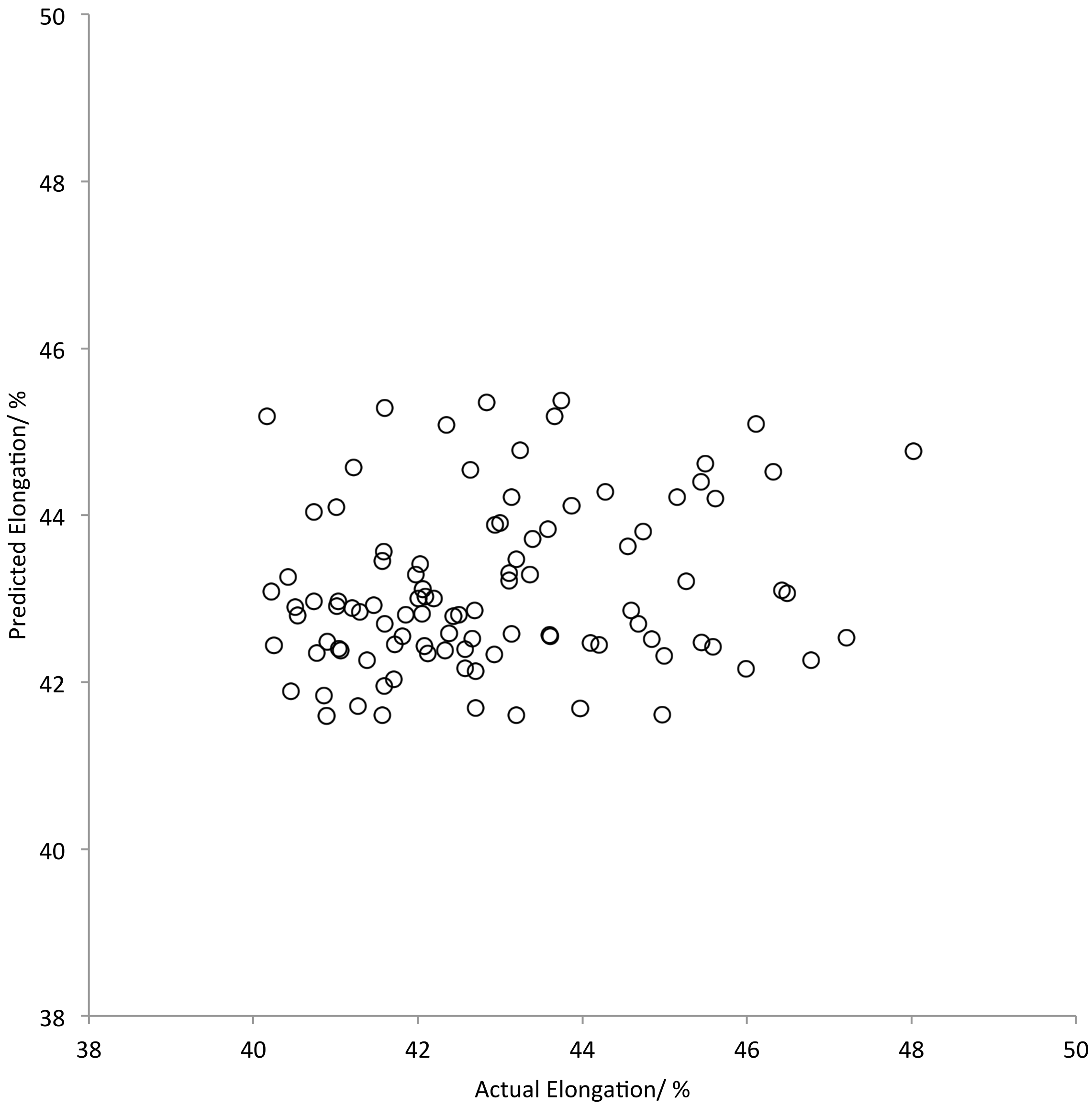


Figure 3.19: Actual elongation values against elongation values predicted by a regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

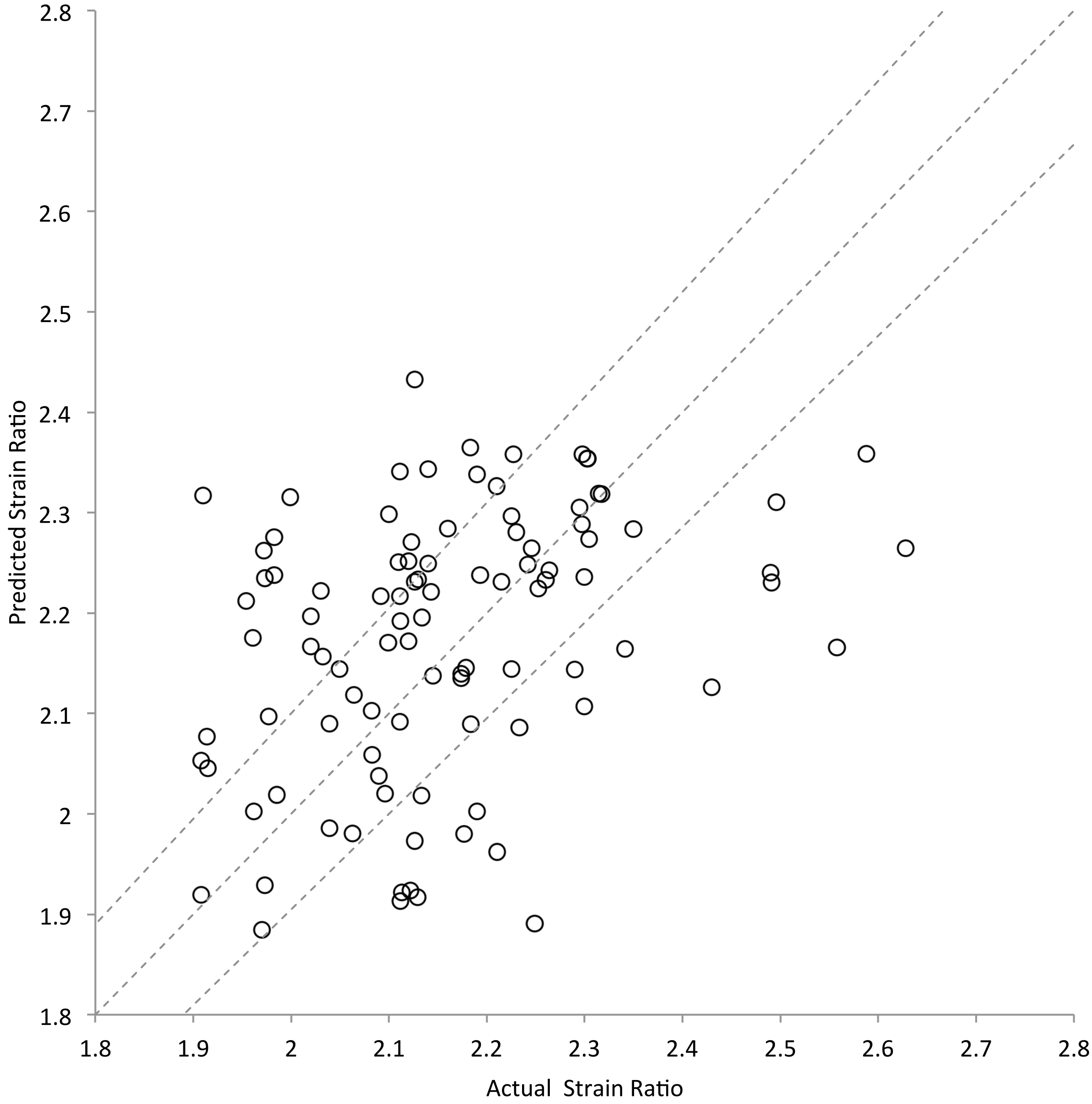


Figure 3.20: Actual strain ratio values against strain ratio values predicted by a regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

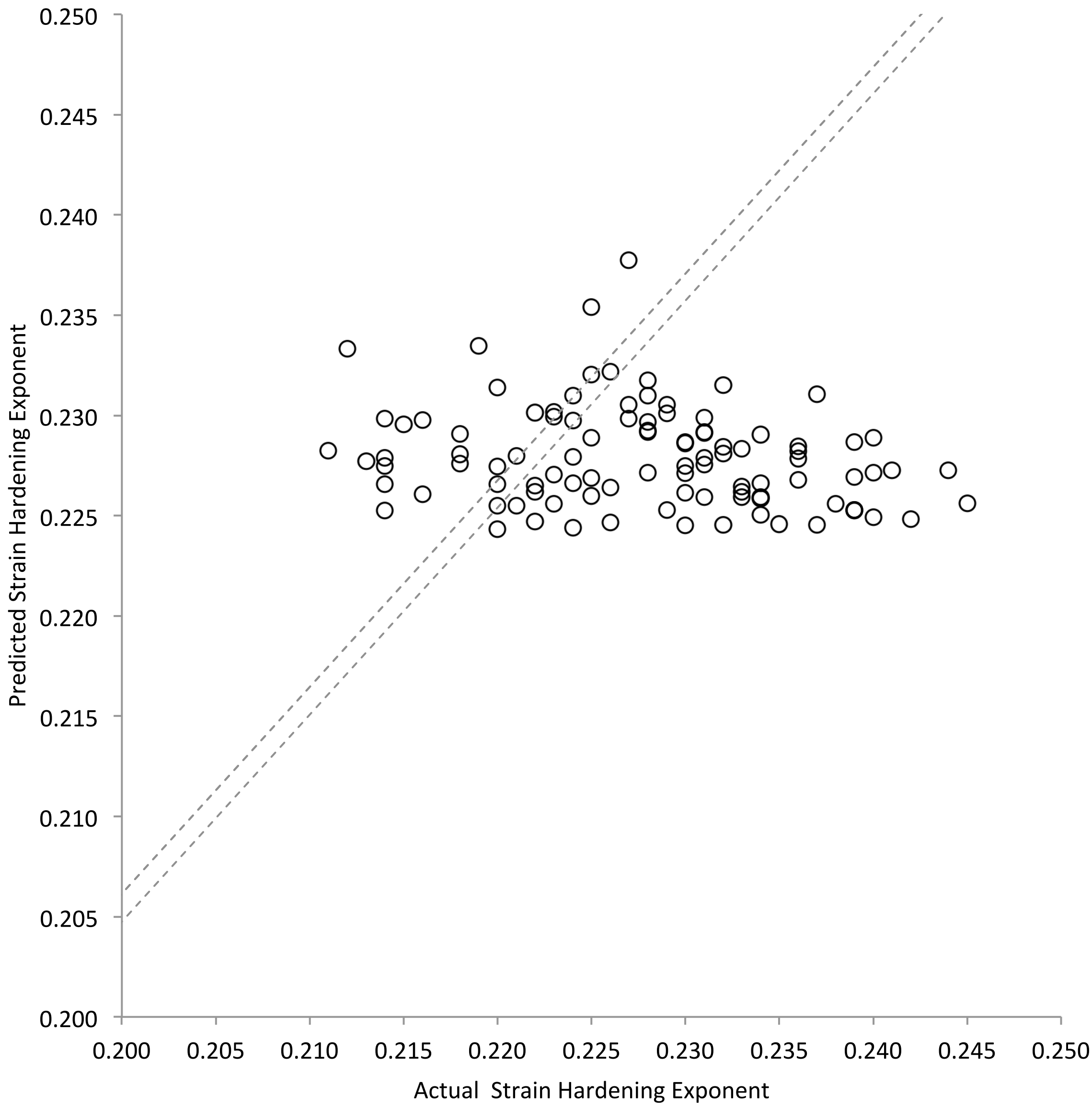


Figure 3.21: Actual strain hardening exponent values against strain hardening exponent values predicted by a regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

Table 3.6: Statistical data produced of validation data set from regression model of steels meeting DC05 specification using inputs chosen based on their correlation coefficients

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	186.6	13.7	3.44%	0.51
Proof stress	151.6	12.3	6.38%	-0.14
Elongation	3.552	1.88	3.49%	0.19
Strain ratio	0.030	0.17	6.22%	0.29
Strain hardening exponent	0.00008	0.009	3.23%	-0.23

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Table 3.7: Regression model coefficients for steels meeting DC05 specification using inputs chosen based on their correlation coefficients

Input	**Rm**	**Re**	**A**	**r**	**n**
Intercept	307.2664	163.4807	43.0965	2.1765	0.2276
Gauge	-2.5031	-0.3524	0.9981	-0.0664	-0.0027
Width		-2.5200		0.0036	0.0000
Weight	-1.2358				
RTF temperature	0.6217		0.1140		
Soak temperature	-0.9466		-0.0410		
CGJC temperature					
HGJC temperature	0.6792	0.7816	0.0619		
ROA temperature	-0.6077	0.4384	-0.0219		
OA temperature				-0.0189	
2C temperature	0.4301				
HGJC rate	0.2566	-1.7247	0.0387	0.0318	-0.0002
Soak time	0.8293	-0.1257	-0.2254	-0.0242	0.0008
Furnace tension	0.7595	-1.1364	0.1326	0.0055	0.0011
Temper mill tension in	0.5640	1.0122	-0.0393	0.0099	-0.0001
Temper mill tension out	-0.0293	0.0359	-0.0279	-0.0227	0.0015
Temper mill load	0.7768	1.0772	0.0595		
Temper mill speed	9.2420	-0.7149	-0.0243	0.0142	-0.0015
Temper mill extension	-8.6658	-0.4651	-0.3603		0.0002
Cold reduction	1.7785	3.1386	-0.1656	-0.0008	0.0002
Hot mill drop temperature					
Hot mill coiling temperature					
Hot mill finish temperature		0.7061			
Hot mill rougher temperature					
Carbon					
Silicon					
Sulphur					
Phosphorus	0.8176				
Manganese					
Nickel					
Copper					
Tin	-1.7250				
Vanadium	-0.0512	1.9109			0.0008
Nitrogen					
Aluminium (total)	-0.0168			0.0066	
Aluminium (soluble)	-0.4283				
Niobium					
Boron					
Titanium				0.0236	
Chromium					
Titanium excess					

As can be seen by the plots of the results, Figures 3.17 to 3.21, and the results in Table 3.6 a reduction in the number of inputs had a significant negative impact on the accuracy of the models.

3.7 Conclusions

Model to predict the properties of continuous annealed steels were developed using a multiple linear regression approach. The initial approach, using all the available data regardless as to whether it met specification or not, produced predictions with a small error value but failed to produce predictions that were of the required accuracy. The range over which the predictions were made was the main cause of this discrepancy. Whilst maintaining a small error value is a goal that should be aimed for with future models the correlation between the predicted results and actual results also needs to be considered as well. Selecting only data that had met the DC05 specifications resulted in a reduction in the reported error of the model as well as an increase in the reported correlation. However it is likely that this increase in the predictive accuracy was most likely due to the reduction in the range that properties were to be predicted over. Attempting to reduce the complexity of the model by using fewer inputs resulted in the accuracy of the models decreasing.

Using multiple linear regression analysis has proven to be an ineffective way of modelling the properties of continuous annealed steels. The linear approximations are not powerful enough to fully describe the annealing process. A more complex non-linear method of analysing the process is needed to fully describe the continuous annealing process.

CHAPTER 4 – PREDICTION OF PROPERTIES USING A GENERALISED REGRESSION NETWORK

4.1. Introduction

Predicting the properties of rolled products continues to be an important research area within the steel industry. While there are examples that rely on additional equipment on the line to produce a prediction [60] many of the proposed methods focus on the use of neural networks or other similar artificial intelligence approaches. It was with this in mind that a similar approach to that taken by Jones [38] was initially investigated as the predictive method for this project. It quickly became clear that this approach would not be suitable for this project as the results being achieved were poor (this initial work is shown in Appendix I). A different approach was required that would produce better predictions, whilst still being compatible with the ground work that had been laid down already.

This chapter describes how a basic modelling approach was developed and implemented. This includes details of the main philosophy behind this approach, how data was pre-processed and the input selection method used.

4.2. Background

The initial concept for this approach would be some form of data mining. This technique stores previous process history, along with the associated mechanical properties, in a database. When a new set of processing conditions is queried the database is searched for previous cases that are as close as possible to the query case. A normal approach may take ten values, five which are slightly higher than the query case and five that are lower. The final properties for the query case are then estimated using the values associated with the matching cases from the database. This type of approach was utilised by Thomas et al [50] to predict the hardenability of heat treated steels. They listed the benefits of their 'database method' as being:

- The approach can be used for a wide range of compositions. For the present work this may allow for several grades to be combined into one model.
- Only a small amount of data is required in the range of interest.
- The method is ready for immediate use once the minimum amount of data has been obtained.
- The method can be easily updated and maintained.
- Confidence intervals can be calculated for each prediction.

Though there were clearly some benefits to this approach it was decided that implementing it may not have been a worthwhile task. Setting up a database and programming the necessary search functions for this task would likely have proved very time consuming. Whilst investigating this approach a similar method was found that performed similar tasks whilst using a network structure. It was also found that this Generalised Regression approach could be used within the Matlab environment, allowing for it to be integrated with previous work.

4.3. Predictive Method Philosophy

In any large industrial process products are produced by repeating the same steps over and over again. If you require a product to have the same properties as the last one then the processing steps need to be the same as those previously carried out. Likewise, if a product has been produced in a similar manner to one produced previously then one may assume that it will have similar properties to that one. It is this assumption that the modelling approach used in this project is based upon; the previous processing history of continuous annealed coils can be used to predict the properties of a newly produced coil.

Clearly this approach needs to be carefully set up, with particular attention being paid to the data sets used to train and populate any models produced. The data set should cover the whole range of possible processing conditions and should be capable of accounting for process drift. This may be through careful selection of its populating data or through the use of a suitable data updating method.

Generalised regression networks are often categorised as a type of artificial neural network, though less data is required to train them than say a back-propagation network [51, 52]. For a given set of inputs the only training that is required is to calculate the appropriate spread value. Though the workings of such networks can be represented using diagrams, in a manner similar to other artificial neural network approaches, they can easily be characterised using some simple equations. The network response (in this case property), Y, to a set of variables (in this case processing conditions), X, can be represented using the following equation [52]:

$$Y(X) = \frac{\sum_{i=1}^{n} Y_i e^{\left(\frac{-D_i^2}{2\sigma^2}\right)}}{\sum_{i=1}^{n} e^{\left(\frac{-D_i^2}{2\sigma^2}\right)}} \tag{4.1}$$

And:

$$D_i^2 = (X - X_i)^T . (X - X_i) \tag{4.2}$$

Where; Y_i is the stored response for set i,

X_i is stored variables that produced the response Y_i

D_i is the distance between the new variables and the stored variables X_i

σ is the spread value

The distance value determines how closely a new set of data matches those stored within the network. Applying limits to this value illustrates the results of there being an exact match or a massive difference between the data sets. Assuming a distance value of zero ($X = X_i$) results in the exponential equating to one. This means that for this case the value carried into the numerator sum with be that of the stored response (Y_i) and the denominator will be one.

When the distance value is very large (±∞) both the numerator and the denominator become zero; the response to this case has no effect on the final response from the whole network.

A simple method to optimise this model is to minimise the error by altering the spread value. A simple routine was set up using Matlab, in particular the *neural network toolbox* and the *fminsearch* function. *fminsearch* is an unconstrained nonlinear optimisation which uses the simplex search method [61]. In order to train the model the data set used was divided into three subsets; modelling, training and validation. The initial data set was sorted randomly before the subsets were assigned, with the first 100 coils making the validation subset and the next 100 forming the training subset. All remaining coils formed the modelling subset. As with the regression approach, the validation subset was only shown to the model when training was complete. The training data set was used to alter the model's parameters.

The modelling subset, being the largest subset, was used to populate the generalised regression network's hidden layer. All further training and later predictions would be based on the relationships between this data and the remaining training data or new coil entries. The training data is run through the complete network and the mean square error of the predictions found. The optimisation routine then alters the spread value of the network according to this error and repeats the process, trying to find the minimum error value. The validation data set is not used to alter the workings of the model and is presented to the model as unseen data in order to assess the effectiveness of the training process.

4.4. Results

The first models to be produced using this method was developed to assess what advantages this approach offered compared to the multiple linear regression approach which was tried previously. For this reason the first grade of steel to be modelled was the DC05/06 steels analysed in the previous chapter. As the best regression results were found using only those grades that had met the required specification it was decided to use this criteria too. Models were produced using the training method detailed previously, with all available inputs being used. These results are shown in Figures 4.1 to 4.5. As in the previous chapter lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results. Statistical data about all the models is shown in table 4.1. Training was carried out on a PC running Windows Seven with a 2.2GHz dual core Intel processor.

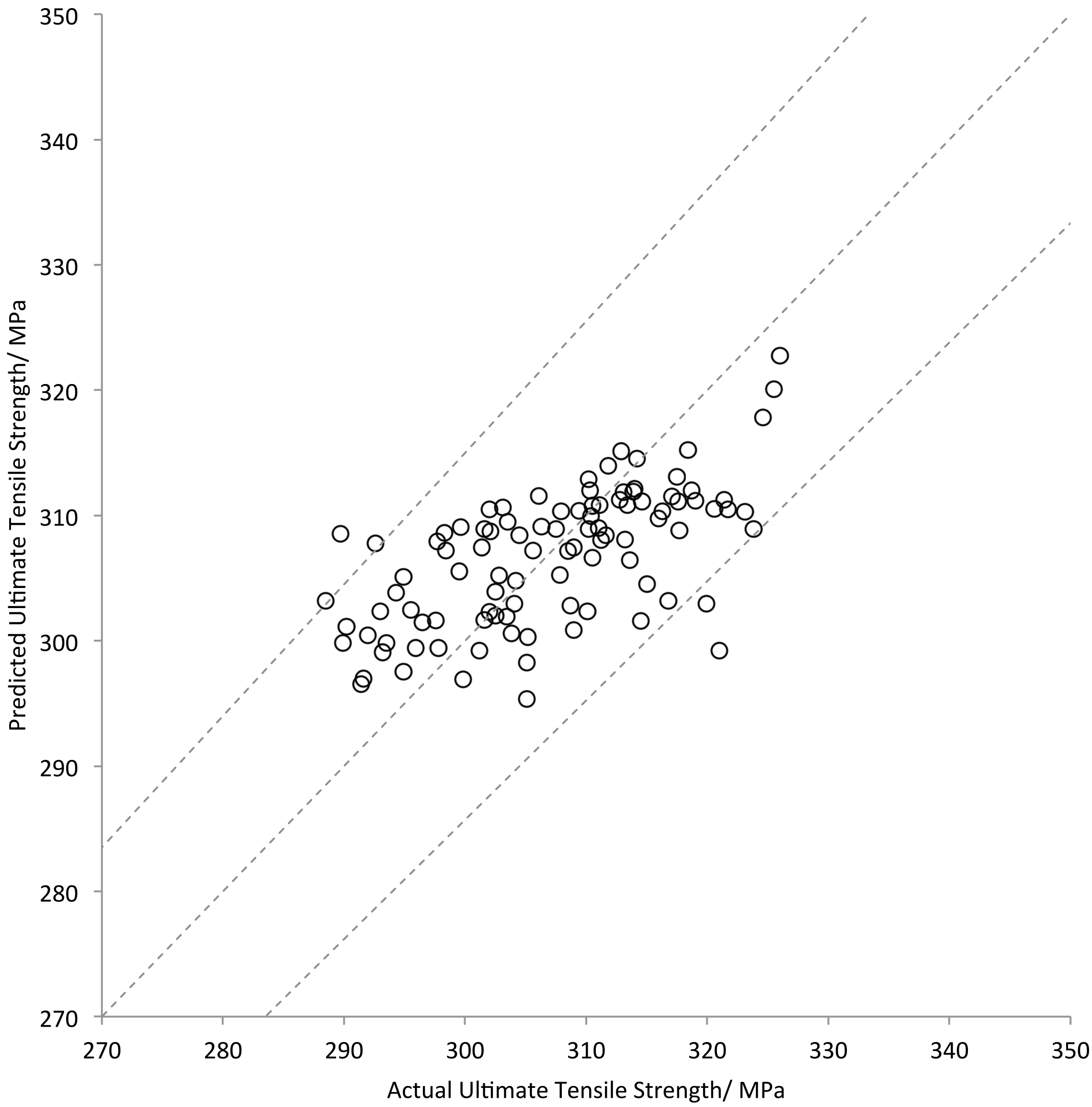


Figure 4.1: Actual proof stress values against proof stress values predicted by a generalised regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

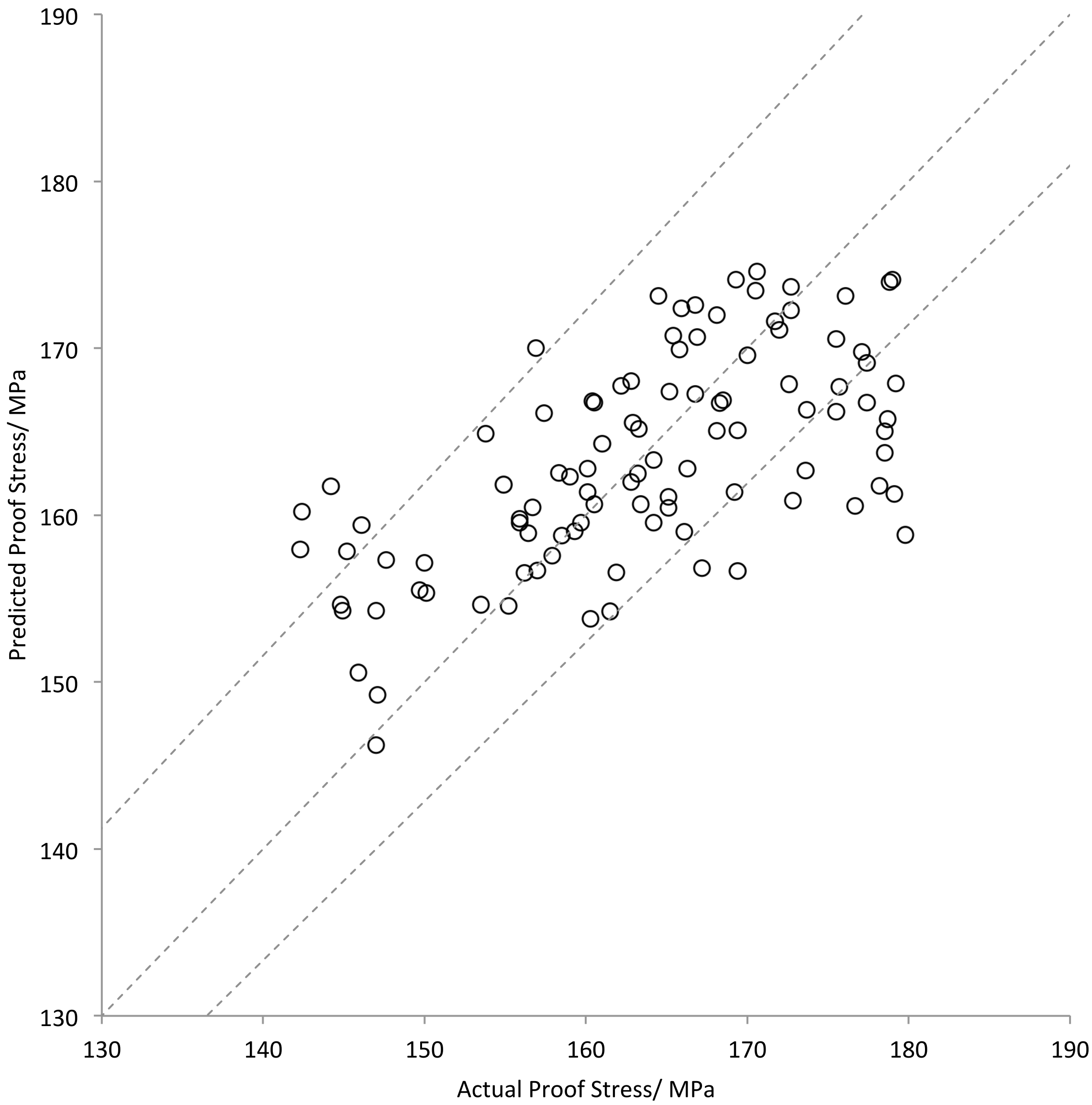


Figure 4.2: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

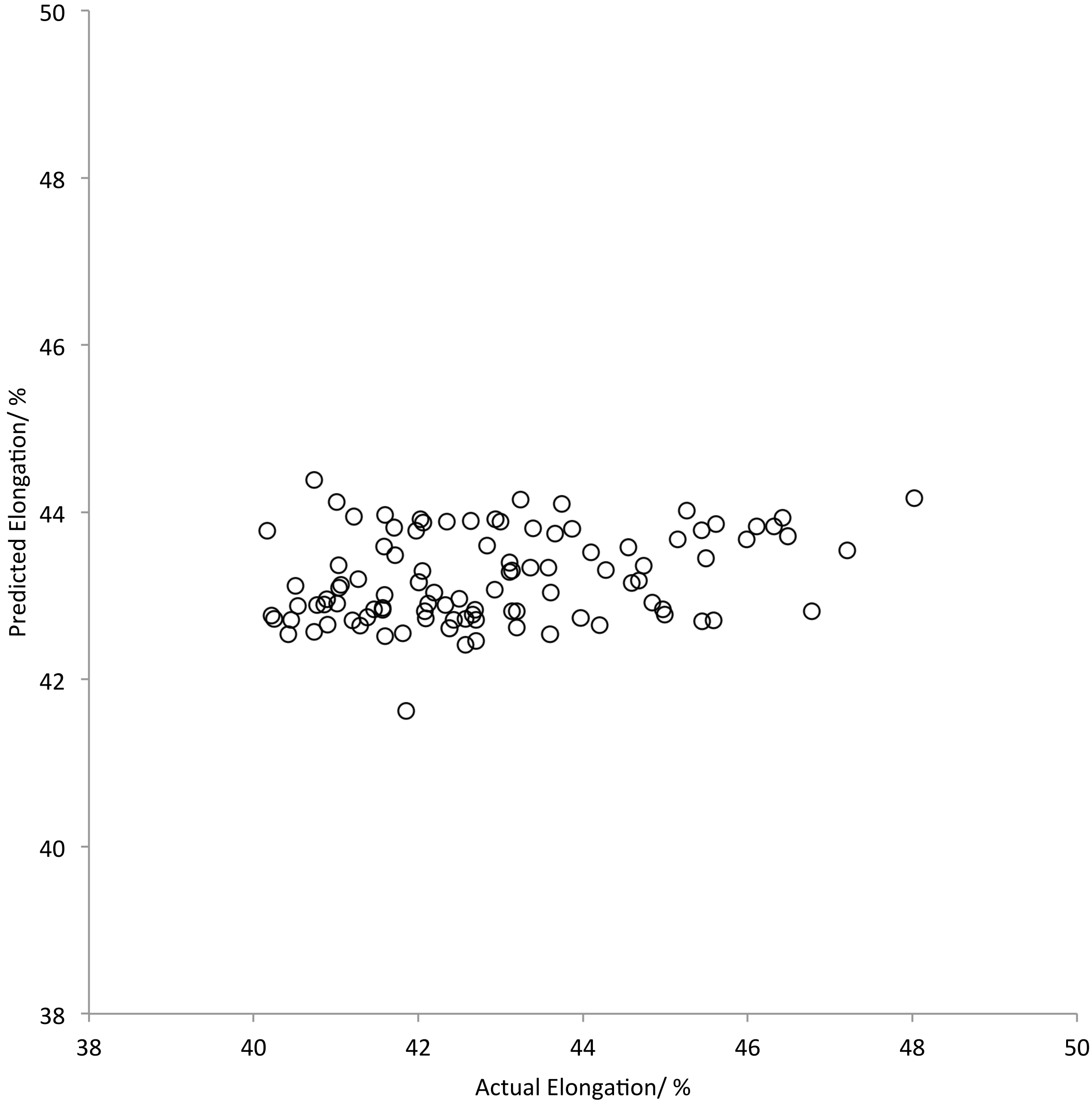


Figure 4.3: Actual elongation values against elongation values predicted by a generalised regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

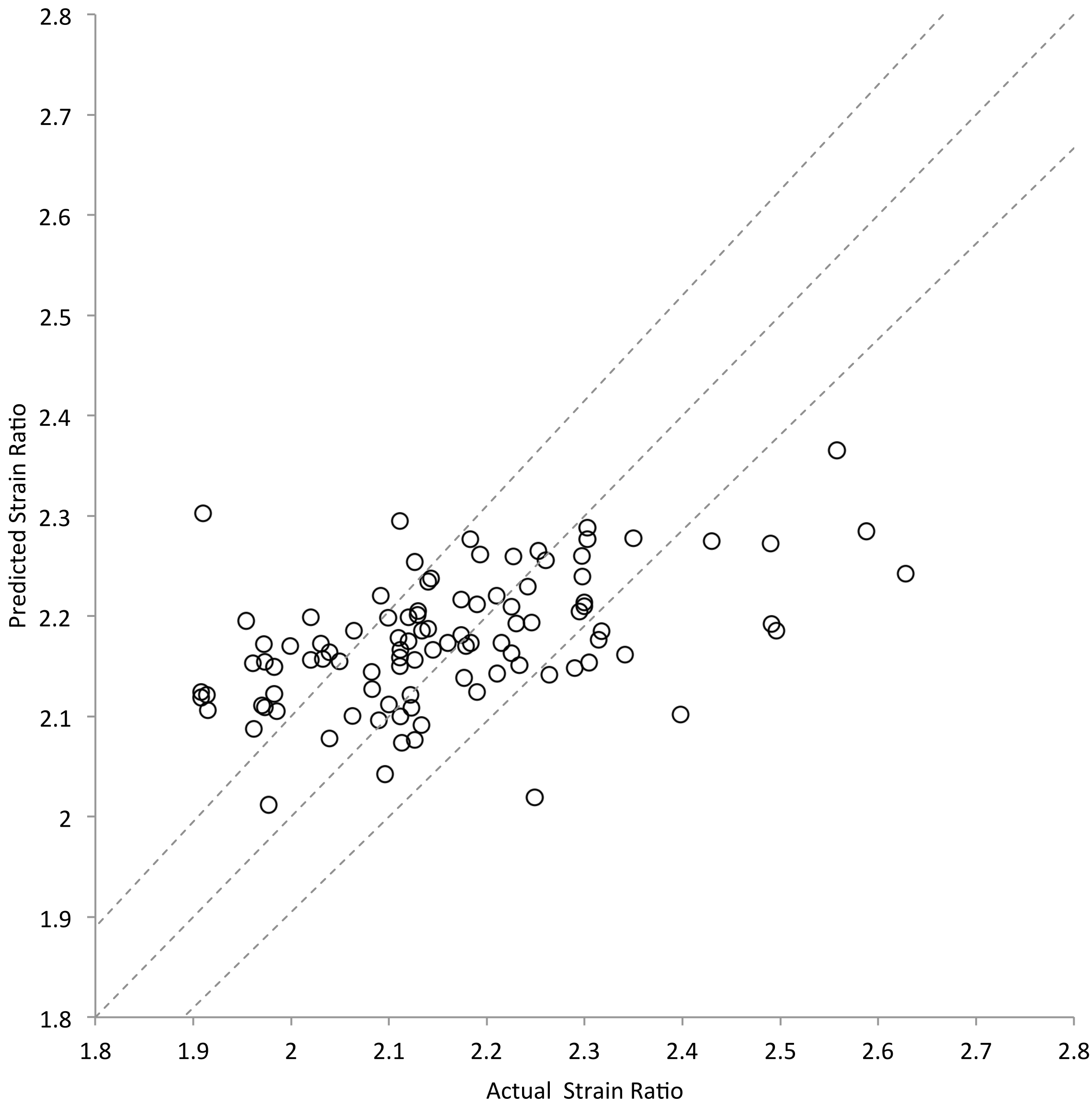


Figure 4.4: Actual strain ratio values against strain ratio values predicted by a generalised regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

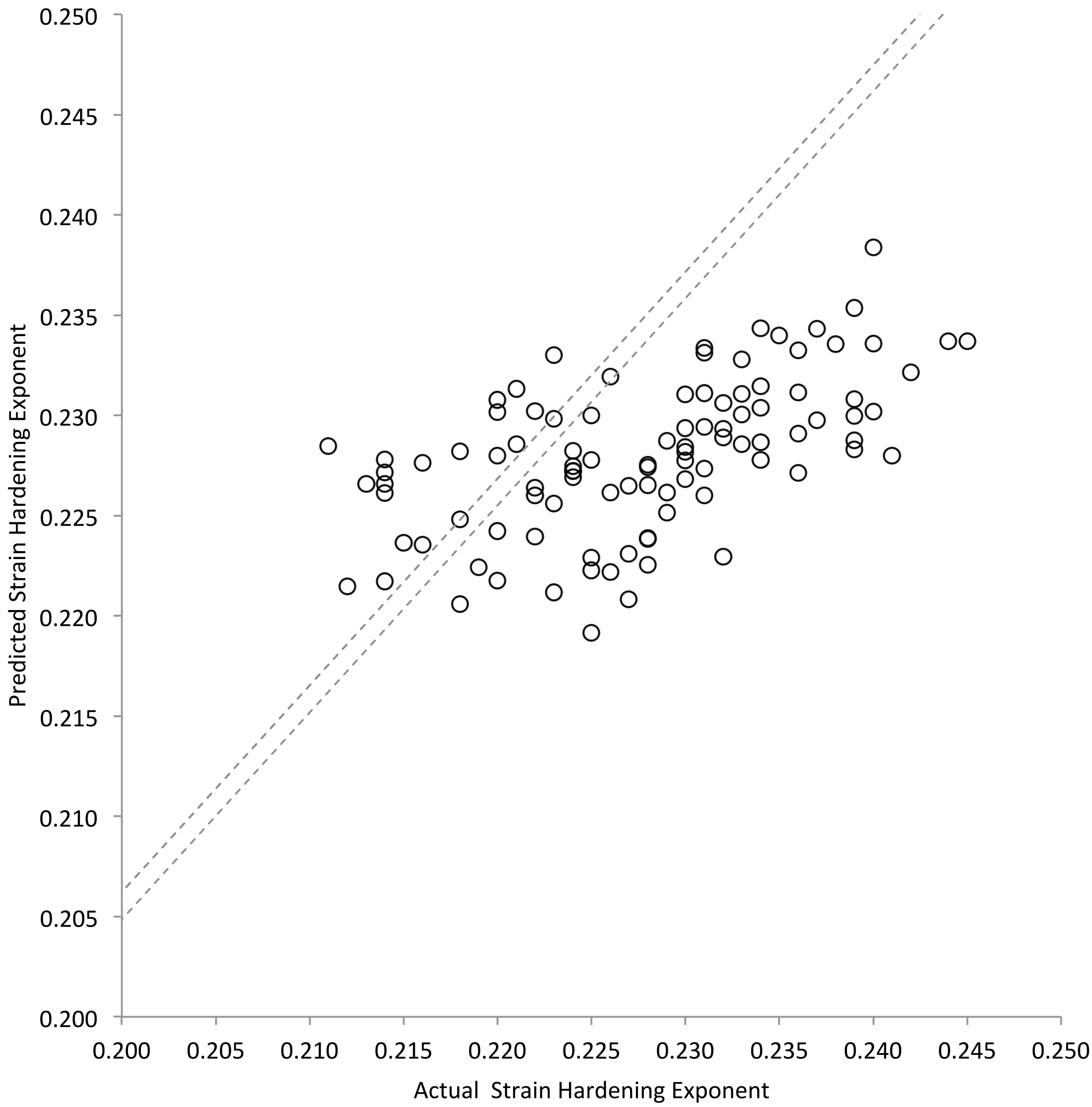


Figure 4.5: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for steels meeting DC05 specification (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

Table 4.1: Statistical data produced from validation data set from generalised regression model of steels meeting DC05 specification

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	53.2	7.3	1.89%	0.63
Proof stress	60.3	7.8	3.70%	0.63
Elongation	3.06	1.75	3.39%	0.29
Strain ratio	0.018	0.13	4.78%	0.49
Strain hardening exponent	0.00004	0.007	2.37%	0.57

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

The spread values for the above models were found to be:

Ultimate tensile strength: 1.9958

Proof stress: 1.7493

Elongation: 2.4263

Strain ratio: 1.9962

Strain hardening exponent: 1.9464

The use of a generalised regression network as the predictive method resulted in an increase in the accuracy of three of the five properties being considered. The elongation and strain ratio predictions saw a slight decrease in the predictive accuracy compared to that of the best regression models. The changes were as follows: ultimate tensile strength 4.1%, proof stress 9.2%, elongation 0.6% (increase), strain ratio 0.05% (increase) and strain hardening exponent 5.6%. As well as a decrease in the mean errors produced by most of the models there was also an increase observed in the correlation values calculated. It is clear that the relationships that exist between some of the input process conditions and output properties are of a higher order than a simple linear regression approach and the generalised regression network was able to pick up on these.

The reasons behind the increase in the error for the elongation and strain ratio models are difficult to pinpoint. Although not directly capable of computing the simple regression approach the generalised regression should be able to replicate the results from it. The small increases in the error suggest that this may well be the case, with the added complications of the network being the main cause of this increase. The elongations predictions appeared to plateau between the values of 42% and 44%. The large spread value that the optimisation routine found for this model is likely to be the main cause of this.

The difficulties predicting the elongation value were reported to the technical experts from Port Talbot. It was their opinion that this may be the result of the failure occurring outside the measured gauge length. The elongation is measured using a device that is attached to the test specimen to mark the gauge length. As the sample extends the device records the extension. If the sample were to break outside the area to which the device is attached, the true extension would not be measured. If the specified value of extension were not obtained, a second sample would need to be tested. However, if the specified value was met, then a retest might not always be carried out, meaning that a lower value of elongation would be recorded than the actual property of the steel. This means that two tests of similar material may result in significant differences in the elongation value. A further complication arises from the fact that elongation values are inherently variable. This is because they result from the plastic instability of the specimen as it is deforms; the onset of necking and hence the elongation vary even for identical specimens of the same material and therefore it will never be possible to predict it a high degree of accuracy.

Whilst using all the available inputs to predict the properties of continuously annealed steels using a generalised regression network the resulting models were considered to be overly large and complicated. In the examples given previously less than 2000 coils were used to populate the models; it is envisaged that as this work progresses more coils will be added to later models. Continuing to use models of this size may lead to longer runtimes. For this reason the effect of reducing the number of inputs to the model was assessed.

Initially the correlation coefficients used previously would form the basis of the input selection method. Although these consider the linear relationship between the properties and the inputs their values where only small, possibly indicating that a non linear relationship may be present. If the correlation coefficient between an input and a property had an absolute value greater than 0.1 the input was selected to model that property. The correlation coefficients were found using a combination of the modelling and training data sub sets so that the validation data did not influence the workings of the model. In addition to inputs selected in this manner other inputs were also included based on the advice of technical staff at Tata Steel. For example, for the interstitial free steels (DC05 and DC06 produced on CAPL) the following inputs were also selected; the soak temperature, soak time, amount of cold reduction, amount of carbon and titanium excess.

These results are shown in Figures 4.6 to 4.10. As in the previous chapter lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results. Statistical data about all the models is shown in table 4.2.

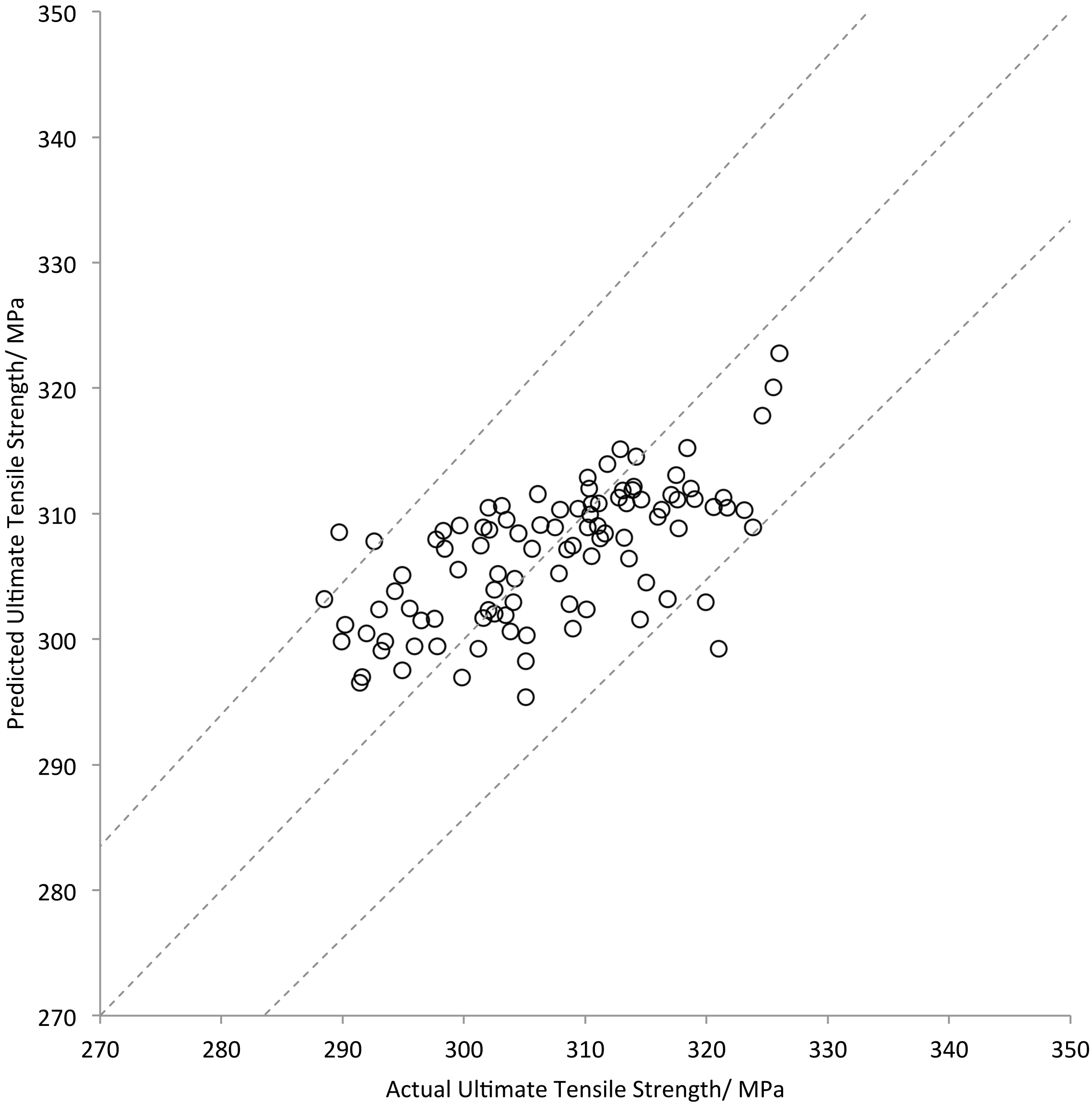


Figure 4.6: Actual proof stress values against proof stress values predicted by a generalised regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

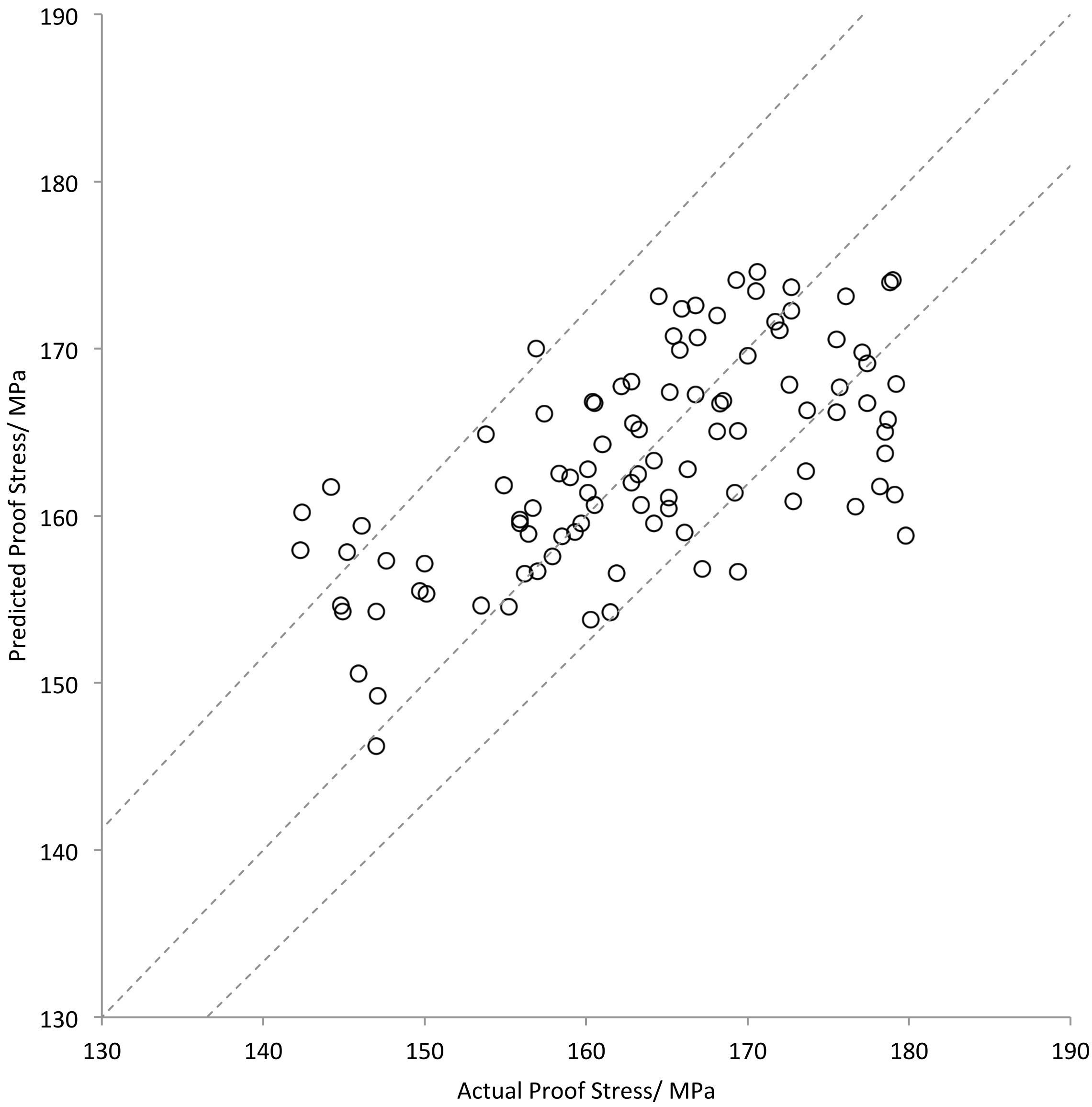


Figure 4.7: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

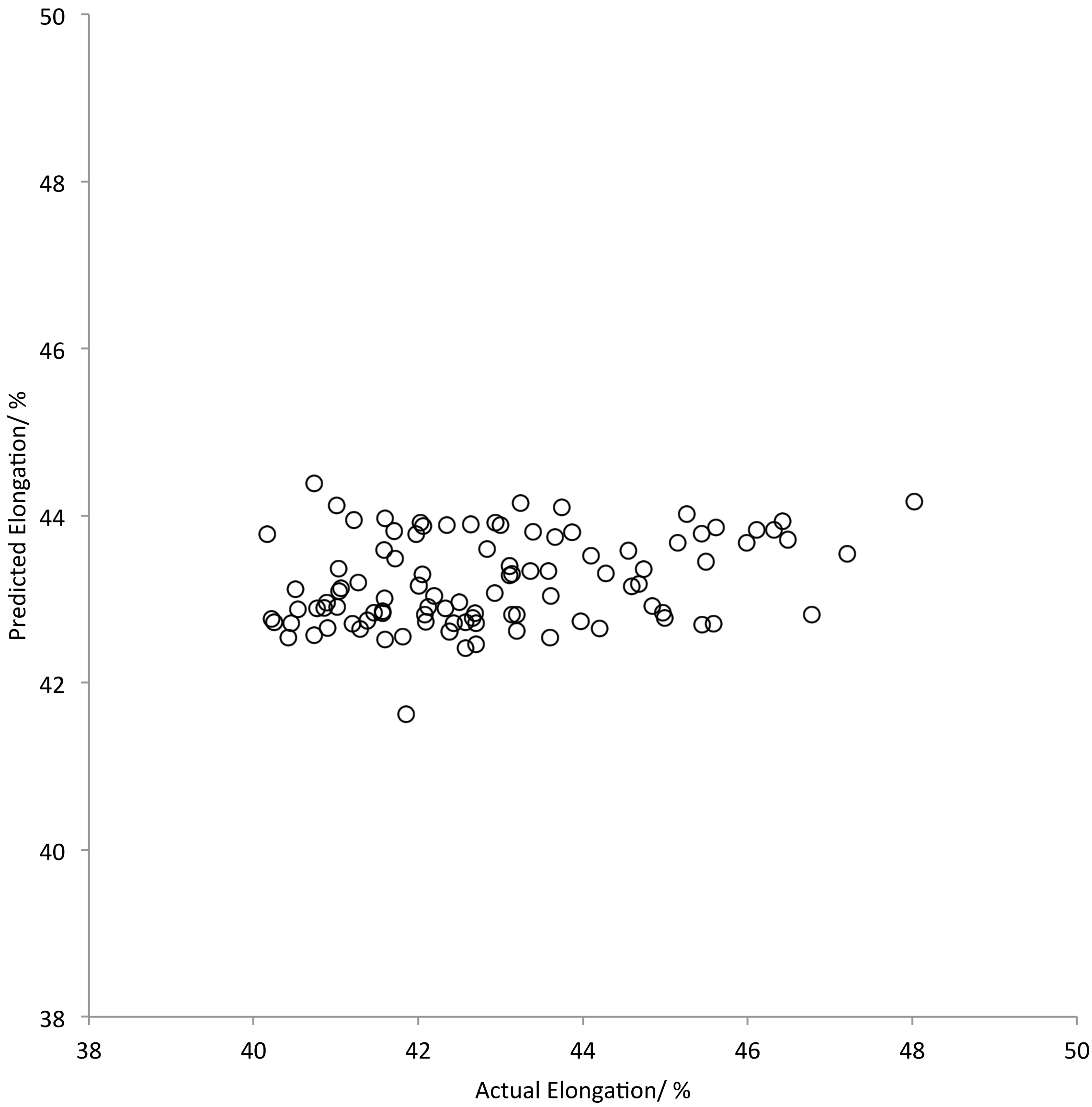


Figure 4.8: Actual elongation values against elongation values predicted by a generalised regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

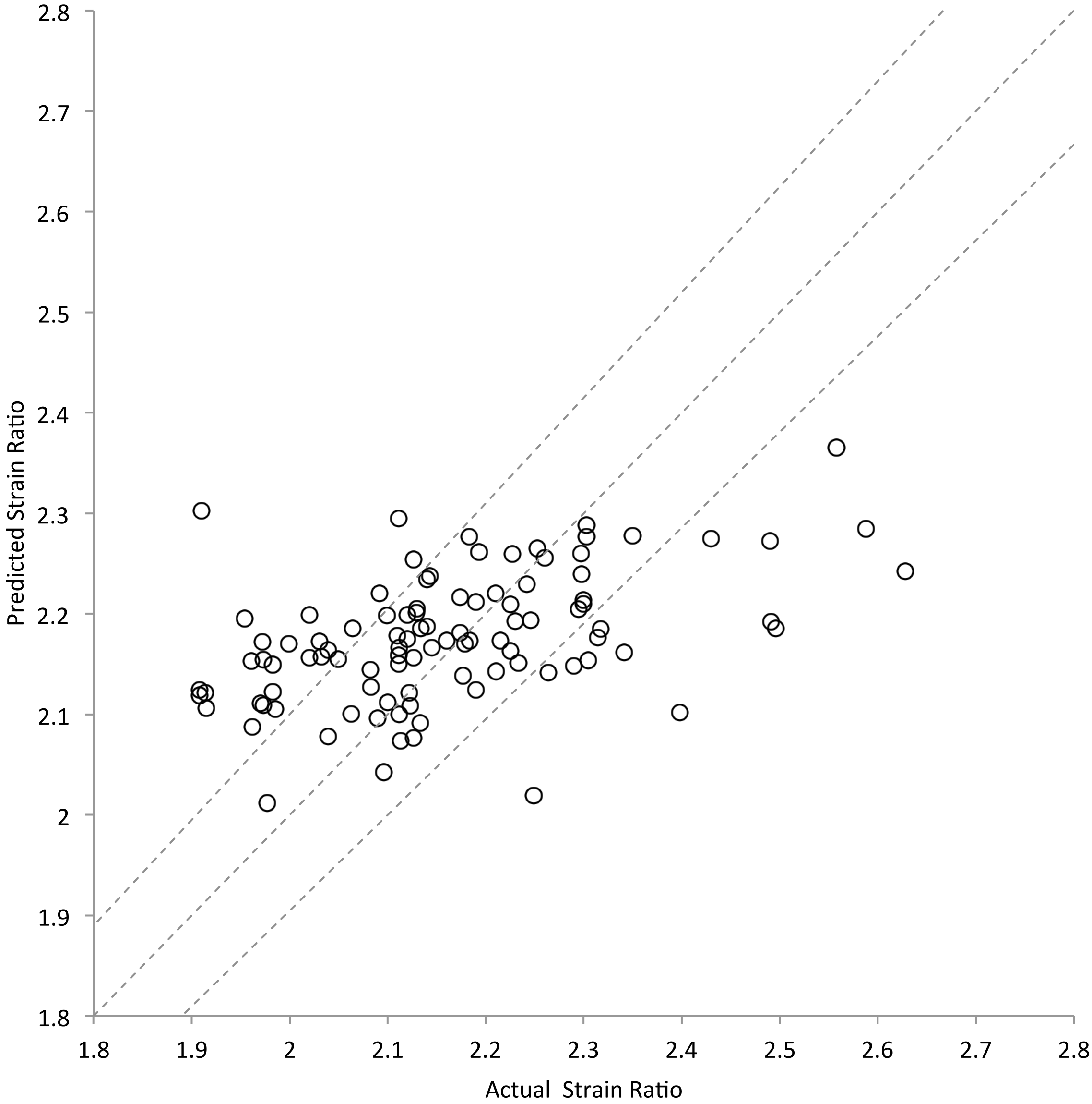


Figure 4.9: Actual strain ratio values against strain ratio values predicted by a generalised regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

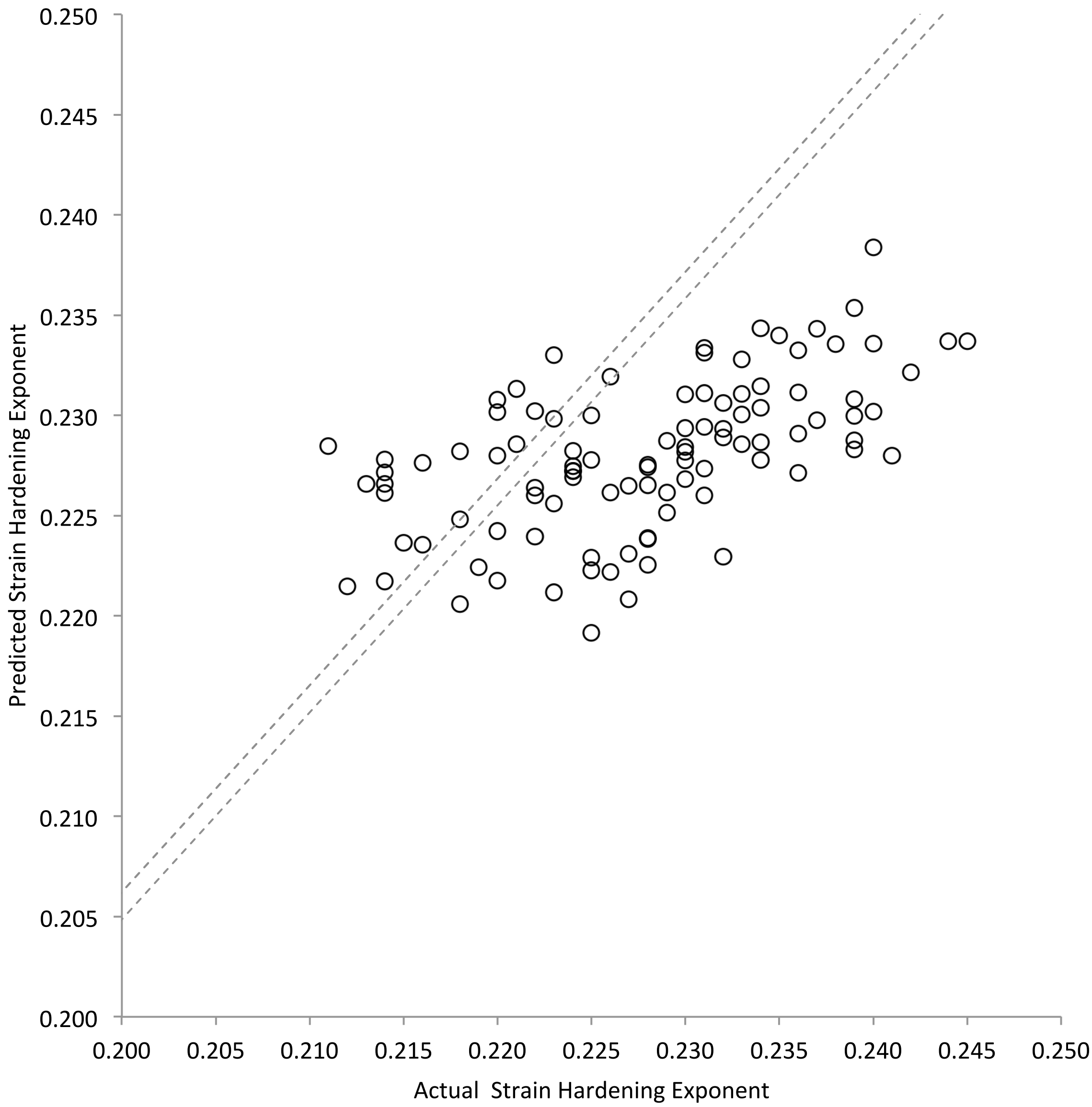


Figure 4.10: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for steels meeting DC05 specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

Table 4.2: Statistical data produced from validation data set from a generalised regression model of steels meeting DC05 specification using inputs chosen based on their correlation coefficients

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	53.2	7.3	1.92%	0.63
Proof stress	70.7	8.4	3.96%	0.57
Elongation	3.11	1.76	3.38%	0.23
Strain ratio	0.019	0.14	4.92%	0.47
Strain hardening exponent	0.00005	0.007	2.50%	0.45

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

The spread values for the above models were found to be:

Ultimate tensile strength:	1.5007
Proof stress:	0.6329
Elongation:	3.5112
Strain ratio:	1.3629
Strain hardening exponent:	1.2435

Reducing the number of inputs to the generalised regression models lead to an increase in the mean percentage error for all properties when compared to the models made using all available inputs. Interestingly the mean square error (the value which model training is based on), and hence the root mean square error, for the ultimate tensile strength model decreased slightly for the new models. Again, all but the elongation value predictions showed an improvement over the best results achieved using the multiple linear regression approach. In most cases the increase in the error was relatively small (with errors still lower than the basic regression approach) however the proof stress is an exception to this observation.

The significant increase in the proof stress error when compared to the error to previous model was accompanied by a decrease in the spread value. A smaller spread value indicates that the model is only using historical data that closely matches the new coil's data. Normally this would imply that one could have a greater confidence in the prediction, due to it being based on more significant (i.e. similar) data. However, the increase in predictive error when compared to the previous model shows that this assumption cannot be made in this case. Rather, the limited input selection has meant that the optimisation routine had to choose a different spread value to minimise the error. Allowing the model to focus more on the nearer historical data instead of the wider approach used previously achieved this. This dramatic change in spread value indicates that selecting the right combination of inputs is a key step in producing a suitable model. While in this case the more selective spread value increased the predictive error it is hoped that different input sets will yield better results. The reduction in the training error for the ultimate tensile strength model indicates that this is possible.

4.5. Use with Other Grades of Steel

The use of a generalised regression network as the main predictive method led to significant increases in the accuracy of models predicting the properties of continuously annealed interstitial free steels. The predictive error increased slightly with a reduction in the number of inputs used. With this in mind it was decided to use the same methodology on a larger data set and to try predicting the properties of a different grade of steel. A sample data set containing the processing information and recorded properties for DC01, DC03 and DC04 steels produced on the continuous annealing line at Port Talbot was used.

The rigor of the specifications for these steels increase with the grade number. If a higher grade fails to meet specification it is downgraded. For this reason the whole data set may be considered as one, with the processing conditions for the entire range being similar. In order to produce a large data set the steels were compared to the DC03 specification. This meant that the final data set represented a large range of DC04 coils, with those failing to meet perhaps just one property specification sill being included. The data set was run through the same cleaning process as detailed before, resulting in there being 19797 coils left with which to develop the model. Table 4.3 shows the maximum, minimum, mean, standard deviation and units of the inputs values and output properties from the cleaned data set.

Table 4.3: DC01/03/04 cleaned data set input conditions and output properties

Quantity	**Max**	**Min**	**Mean**	**Std**	**Unit**
CA Gauge	2.04	0.38	1.02	0.37	mm
CA Width	1830	821	1163	198	mm
CA Weight	51.33	2.48	14.52	4.50	tonnes
Radiant Tube Furnace (RTF) (average)	842.63	652.48	729.29	21.78	^oC
Soak (average)	797.63	639.47	727.68	19.77	^oC
Controlled Gas Jet Cooling (CGJC) (average)	878.18	600.00	658.10	12.07	^oC
High Gas Jet Cooling (HGJC) (average)	472.94	257.88	398.50	36.62	^oC
Reheat Overage (ROA) (average)	480.37	299.92	415.73	23.94	^oC
Overage (average)	366.39	127.13	251.36	47.80	^oC
Second Cooling (average)	250.00	105.52	209.44	9.25	^oC
HGJC Rate	160.4	13.0	55.2	13.0	$^oC/s$
Soak Time	763	38	61	21	s
Furnace Tension	13.9	1.4	5.3	2.5	kN
Temper Mill Tension In (TMTI)	125.4	28.7	57.4	17.0	kN
Temper Mill Tension Exit (TMTE)	122.0	28.5	57.0	16.9	kN
Temper Mill Load (TML)	988.4	2.1	328.0	158.9	tonnes
Temper Mill Speed (TMS)	474.6	35.4	317.3	76.4	m/min
Temper Mill Extension (TME)	2.058	0.072	0.838	0.083	%
Cold Reduction	0.974	0.033	0.674	0.101	%
Hot Rolled Drop Temperature	1318	127	1212	33	^oC
Hot Rolled Coil Temperature	767	465	659	31	^oC
Hot Rolled Finishing Temperature	953	821	899	13	^oC
Hot Rolled Stand 5 Temperature (HRS5)	1156	923	1091	23	^oC
Carbon (C)	0.192	0.002	0.025	0.013	%wt
Silicon (Si)	0.391	0.001	0.003	0.015	%wt
Sulphur (S)	0.032	0.003	0.015	0.003	%wt
Phosphorus (P)	0.082	0.004	0.011	0.004	%wt
Manganese (Mn)	1.448	0.062	0.193	0.101	%wt
Nickel (Ni)	0.040	0.009	0.015	0.003	%wt
Copper (Cu)	0.088	0.007	0.022	0.007	%wt
Tin (Sn)	0.040	0.001	0.006	0.003	%wt
Vanadium (V)	0.003	0.001	0.001	0.000	%wt
Nitrogen (N)	0.014	0.001	0.003	0.001	%wt
Aluminium (Al) (total)	0.074	0.009	0.035	0.005	%wt
Aluminium (Al) (soluble)	0.068	0.009	0.032	0.005	%wt
Niobium (Nb)	0.059	0.001	0.001	0.003	%wt
Boron (B)	0.004	0.000	0.003	0.001	%wt
Titanium (Ti)	0.062	0.001	0.001	0.002	%wt
Chromium (Cr)	0.060	0.004	0.018	0.005	%wt
Titanium Excess (Ti*)	0.025	-0.817	-0.132	0.054	
Ultimate Tensile Strength (Rm)	361.0	278.1	324.2	9.3	N/mm^2
Proof Stress (Re)	239.9	150.3	219.6	14.7	N/mm^2
Elongation (A)	51.58	34.01	40.83	2.30	%
Strain Ratio (r)	2.625	1.301	1.620	0.203	
Strain Hardening Exponent (n)	0.256	0.169	0.216	0.010	

Models of the DC01/03/04 steels were produced using the same method detailed above. The data set was then divided into the same subsets as before (100 coils in the validation and training subsets); leaving considerably more coils in the modelling subset then had been used previously. Due to the large size of the data set only inputs that had a correlation coefficient of greater than 0.1. The outputs of these models are shown in Figures 4.11 to 4.15. Error lines showing ±5% have been superimposed on to these results and statistical data about all the models is collated in table 4.4.

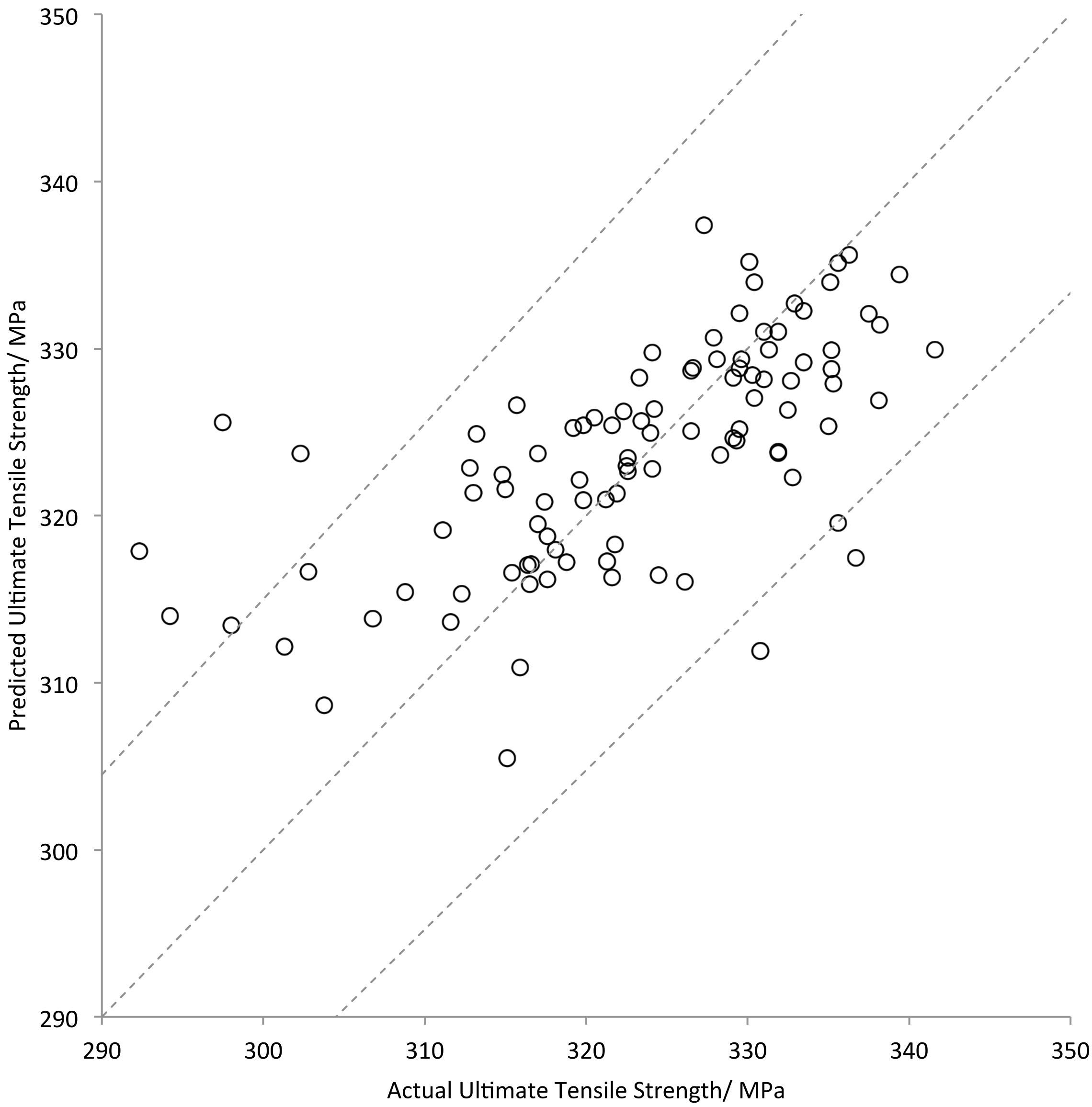


Figure 4.11: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for DC01/03/04 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 0.5821. The following inputs were chosen:

Physical: gauge, width and cold reduction

CAPL: radiant tube furnace temperature, soak temperature, controlled gas jet cooling temperature, high gas jet cooling temperature, reheat overage temperature, overage temperature, HGJC rate, soak time, furnace tension, temper mill tension in, temper mill tension out, temper mill speed and temper mill extension

Hot Rolling: finishing temperature and coiling temperature

Chemistry: carbon, phosphorus, manganese, nitrogen and titanium excess

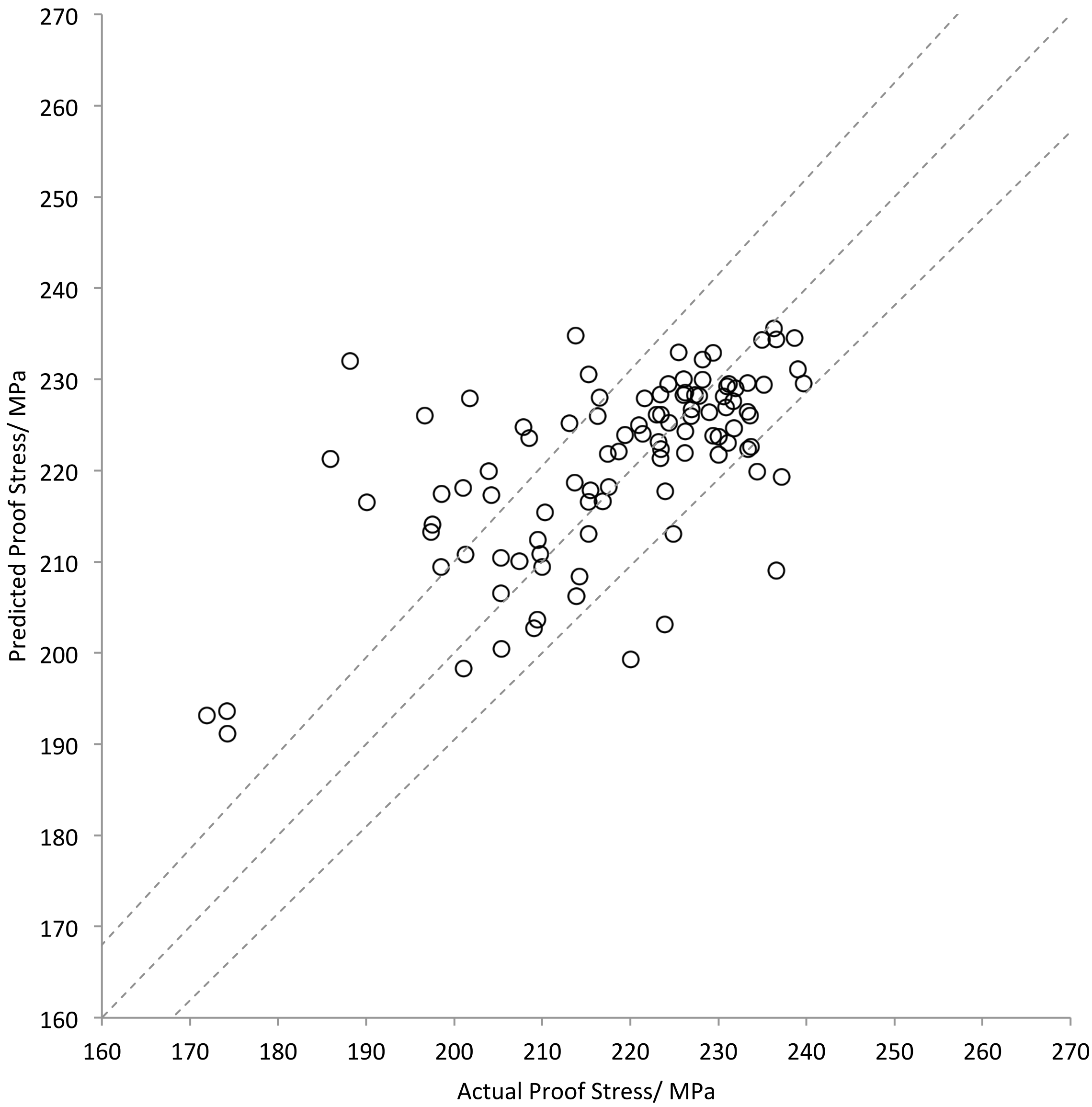


Figure 4.12: Actual proof stress values against proof stress values predicted by a generalised regression model for DC01/03/04 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the proof stress model was found to be 0.2840. The following inputs were chosen:

Physical:	cold reduction
CAPL:	radiant tube furnace temperature, high gas jet cooling rate temperature, reheat overage temperature, overage temperature, soak time and temper mill speed
Hot Rolling:	rougher temperature and coiling temperature
Chemistry:	carbon, manganese and titanium excess

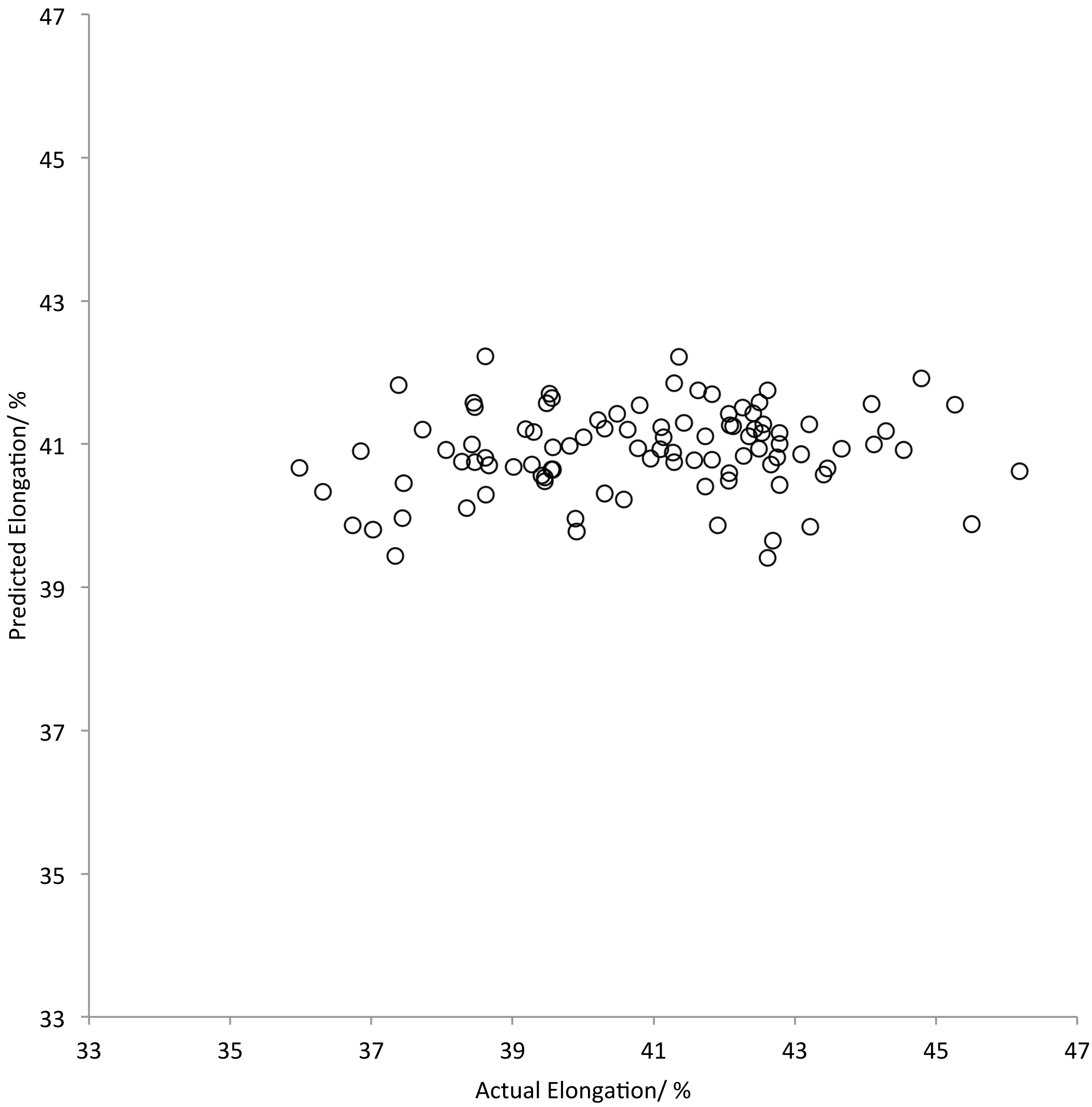


Figure 4.13: Actual elongation values against elongation values predicted by a generalised regression model for DC01/03/04 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the elongation model was found to be 0.4104. The following inputs were chosen:

Physical: cold reduction

CAPL: radiant tube furnace temperature, soak temperature, controlled gas jet cooling temperature, high gas jet cooling temperature and soak time

Hot Rolling:

Chemistry: carbon manganese and titanium excess

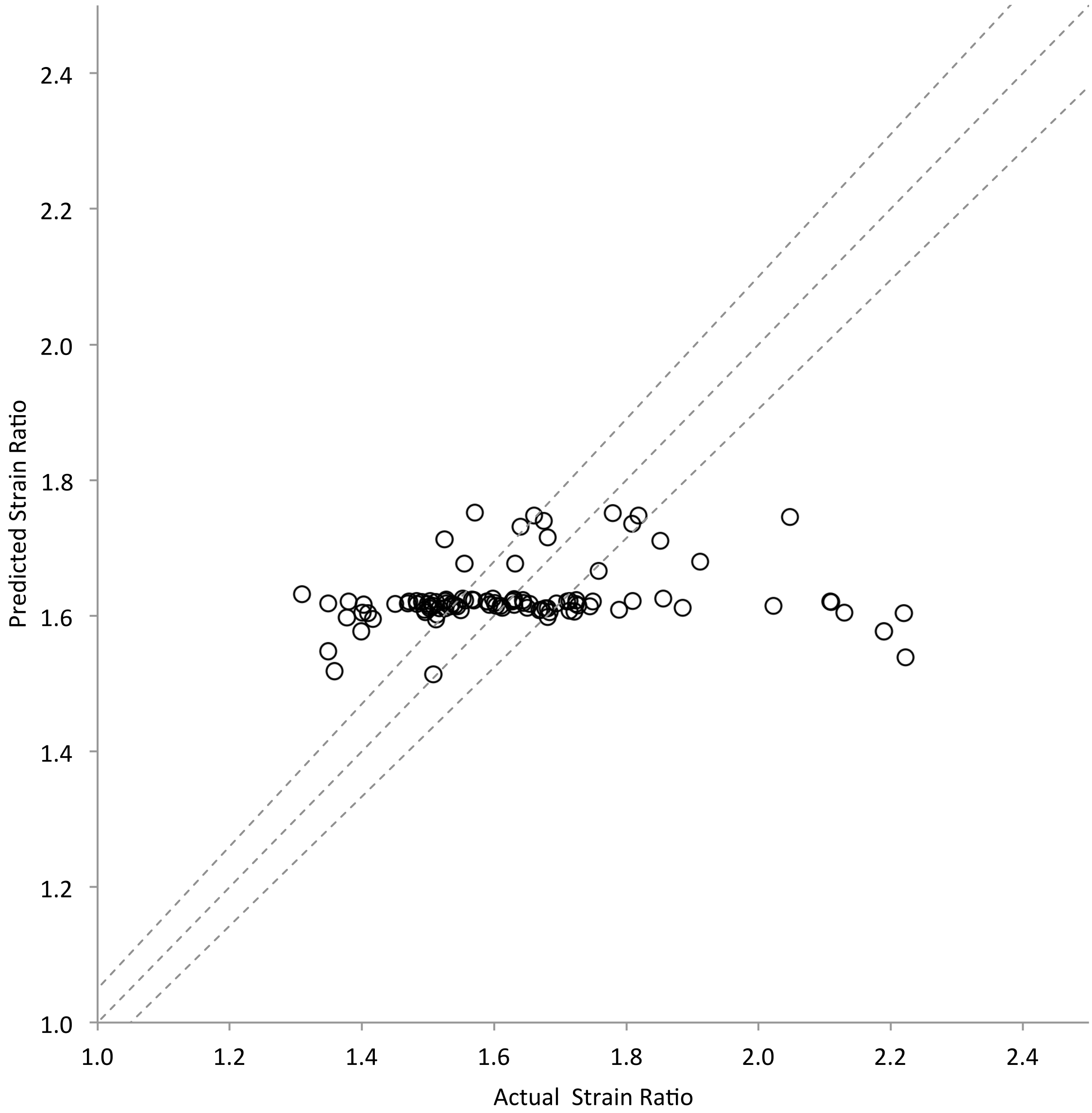


Figure 4.14: Actual strain ratio values against strain ratio values predicted by a generalised regression model for DC01/03/04 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 1.3148. The following inputs were chosen:

Physical: gauge and cold reduction

CAPL: radiant tube furnace temperature, soak temperature, high gas jet cooling temperature, reheat over age temperature, soak time and furnace tension

Hot Rolling:

Chemistry: carbon, manganese and titanium excess

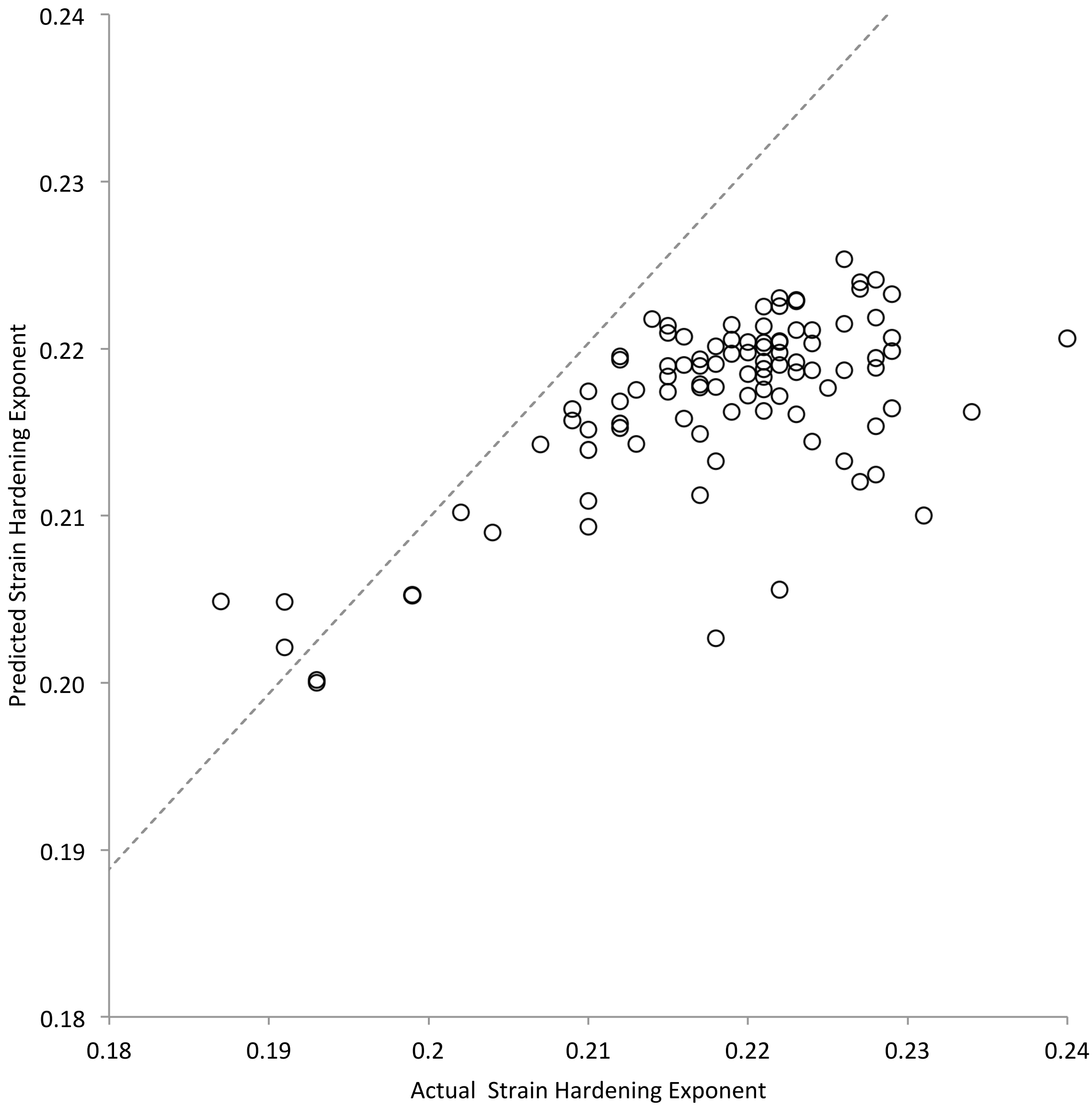


Figure 4.15: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for DC01/03/04 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain hardening exponent model was found to be 1.1483. The following inputs were chosen:

Physical:	gauge, width and cold reduction
CAPL:	radiant tube furnace temperature, soak temperature, high gas jet cooling temperature, reheat overage temperature, second cooling temperature, HGJC rate, soak time, furnace tension, temper mill tension in, temper mill tension out, temper mill load and temper mill speed
Hot Rolling:	
Chemistry:	carbon, manganese and titanium excess

Table 4.4: Statistical data produced from validation data set from a generalised regression model of DC01/03/04 steels meeting specification using inputs chosen based on their correlation coefficients

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	63.5	8.0	1.78%	0.66
Proof stress	137.5	11.7	3.96%	0.63
Elongation	5.50	2.35	4.63%	0.15
Strain ratio	0.036	0.19	8.04%	0.17
Strain hardening exponent	0.00005	0.007	2.46%	0.67

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

The increased data available to model the DC01/03/04 steels did not lead to any significant increase in the predictive accuracy of the models developed from it. As with the previous grade, models predicting the ultimate tensile strength, proof stress and strain hardening exponent produced better results than the elongation and strain ratio models. Interestingly, the predictions from the strain ratio model exhibited a distinct plateau, similar to that seen with the elongation models produced previously. This was not observed for the other grade.

One point of interest was the decreased spread values that were found for some of the new models. The ultimate tensile strength and elongation models in particular were found to have a considerably smaller spread values than models of the same properties focusing on other grades. The increase in the number of coils used for the DC01/03/04 models is likely to be the main reason for this change. The greater number of coils for the new model to use may mean that the model does not need to look as far from a new entry as it previously might have to find similar coils with which to make a prediction.

The model failed to accurately predict the strain ratio for this grade of steel. Whilst the predictive accuracy for other grades is not as high for this property as others there was still some agreement between the actual and predicted values. The same plateau effect was observed in the predictions of the elongation using previous models and was attributed to the large spread value selected by the training process. This represents one possibility, though the spread value was no larger than previous strain ratio models (indeed in one case smaller). The strain hardening exponent model for the DC01/03/04 steels had a similar spread value and was able to produce more accurate results, further discrediting the possibility.

The increase in the number of coils used to produce a generalised regression models failed to deliver the increase in predictive accuracy. When used with the DC01/03/04 grades this approach lead a decrease in the strain ratio model's accuracy as compared to other grades. Given these issues thought it was felt that continued development of these models was worthwhile. Models predicting the ultimate tensile strength, proof stress and strain hardening exponent produced results which suggest the model is capable of predicting some of the properties of these grades. As with previous the previous grades it was believed that further refinement of the model inputs would help produce results of the required accuracy.

4.6. Use with Other Process Lines

Tata steel operates a metallic coating line, Zodiac, at their plant in Llanwern. This line is comprised of an annealing furnace and a hot dip bath for applying the metallic coating (normally zinc) to the steel. It was hoped that the techniques developed to predict the properties of steels produced at Port Talbot could be transferred to the Llanwern plant as well. A simplified diagram of the Zodiac line is shown in Figure 4.16.

Due to financial difficulties during the 1990s blast furnace, steel making and casting facilities at Llanwern were shut down leaving the hot mill and cold mill. Coils that are processed on Zodiac therefore are formed from slabs that originate from Port Talbot. The slabs can either be hot rolled at Port Talbot or Llanwern. There are some differences between the hot rolling lines at the two facilities, in particular the rougher configuration and coil box at Port Talbot; however the key process conditions are the same for each line. The differences between the continuous annealing line at Port Talbot and Zodiac at Llanwern mean that the possible inputs to the model vary.

These differences meant that some parts of the model training routine would have to be rewritten in if the Zodiac data was to be used. The Port Talbot model is given forty process conditions that it can use as possible inputs, these are initially selected using an importing tool that is separate to the main training routine. This presented two possible ways of making models of the Llanwern data. The first of these would involve written an entirely new training model and importing tool, using the methods learned developing the work for Port Talbot. The second option involved writing a new importing tool for the Llanwern data that produced an output the same size as the one designed for the Port Talbot data, i.e. one that selected forty initial inputs for the training routine to use. Whilst the first method would produce optimal results and cover every possible process condition it would also require a considerable amount of time and effort to compile. The second method would be straight forward to compile but relied on careful decisions to be made in regards to which inputs it would choose.

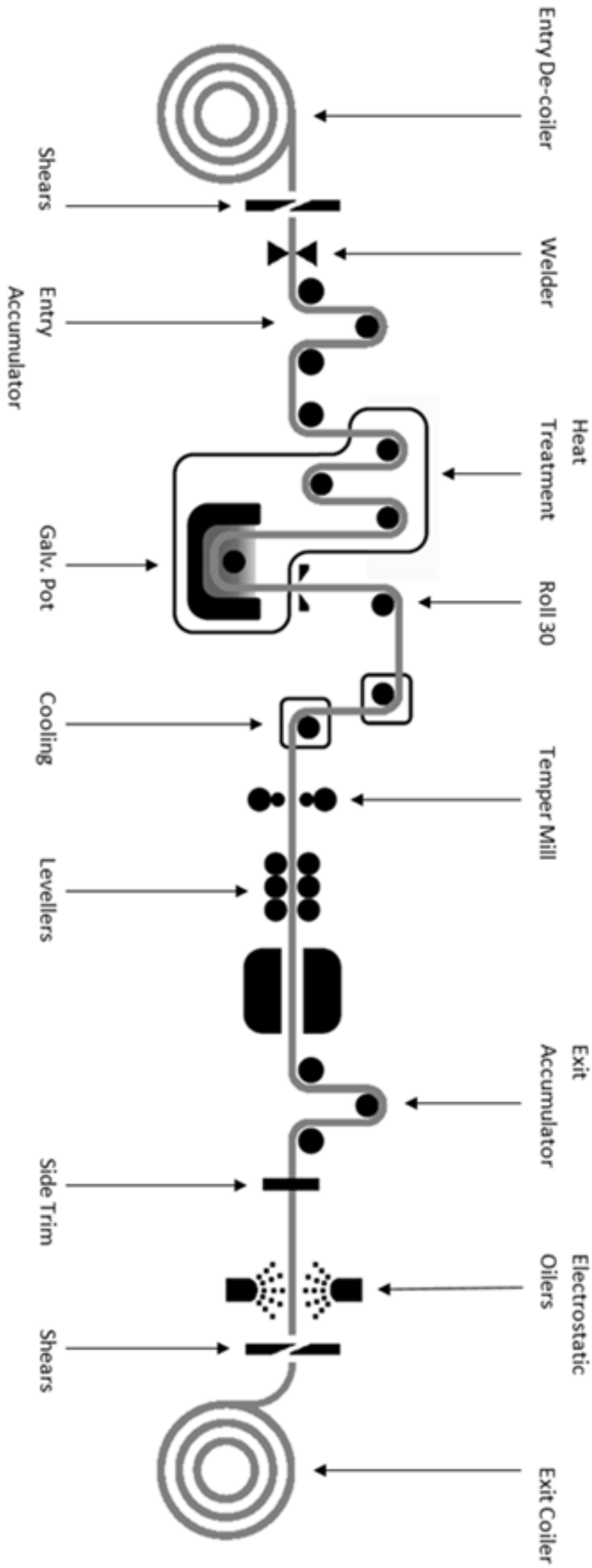


Figure 4.16: Simplified diagram of the ZODIAC line at Tata Steel's Llanwern plant [11]

As the chemistry details and heat treatments prior to annealing remained the same as the Port Talbot data only inputs from the annealing line would need to be considered. Upon reviewing the possible inputs from Zodiac it was found that the process could be covered using the same number of inputs as Port Talbot. This meant that a new importing tool was the only thing that needed to be developed. The main changes related to areas where temperatures were measured. Of these three were of particular interest, these being: the pot, snout and roll 30 temperatures. The pot and snout temperatures relate to the hot dip section of the line. The roll 30 temperature measures the strip temperature at the top of the drying phase that follows the strip leaving the hot dip bath.

To produce models based on the Zodiac line a data set was obtained containing information on 3004/3005 grades. These grades have similar properties to the DC05/DC06 steels produced at the Port Talbot but with an additional metallic coating. A data set containing the process conditions for the Zodiac line was obtained. Using the 'coil ID' value this data was linked to the associated processing conditions from the Port Talbot plant, producing a complete set of data for the grades. The data set was run through the same cleaning process as detailed before, resulting in there being 6816 coils left with which to develop the model. Table 4.5 shows the maximum, minimum, mean, standard deviation and units of the inputs values and output properties from the cleaned data set.

Table 4.5: 3004/05 cleaned data set input conditions and output properties

Quantity	**Max**	**Min**	**Means**	**Std**	**Unit**
Gauge	2.02	0.53	0.91	0.29	mm
Width	1766	851	1291	206	mm
Weight	30.00	2.73	14.60	4.44	tonnes
Direct Fire (DF) (average)	765.34	641.55	715.18	14.83	^oC
Radiant Tube Furnace Start (RTFS) (average)	886.50	401.25	833.06	17.82	^oC
Snout (average)	501.09	447.72	467.17	6.15	^oC
Water Quench (WQ) (average)	159.93	50.07	85.01	22.47	^oC
Coating Weight	147.70	37.89	68.88	11.34	g/m^2
Length	4889	240	1732	678	m
Line Speed	129.48	39.00	93.32	17.12	m/min
Temper Mill Load (TML)	168.97	-51.46	80.40	22.73	kN
Temper Mill Tension In (TMTI)	7971.00	1676.78	4103.29	1092.34	KN
Hot Rolled Drop Temperature	1288	94	1217	32	^oC
Hot Rolled Coiling Temperature	758	621	682	4	^oC
Hot Rolled Finishing Temperature	949	890	914	4	^oC
Hot Rolled Stand 5 Temperature (HRS5)	1163	1008	1100	21	^oC
Cold Reduction	0.868	0.592	0.766	0.046	%
Hot Dip Pot Temperature (average)	476.82	452.11	461.29	3.27	^oC
Roll 30 Temperature (average)	203.85	120.00	148.26	20.23	^oC
Radiant Tube Furnace End (RTFE) (average)	900.00	400.46	835.31	15.57	^oC
Temper Mill Tension Out (TMTO)	7313.64	2022.79	3846.80	887.42	kN
Molybdenum (Mo)	0.0080	0.0010	0.0012	0.0006	%wt
Arsenic (As)	0.0020	0.0010	0.0011	0.0002	%wt
Carbon (C)	0.1410	0.0012	0.0025	0.0041	%wt
Silicon (Si)	0.1580	0.0010	0.0032	0.0048	%wt
Sulphur (S)	0.0170	0.0049	0.0096	0.0022	%wt
Phosphorus (P)	0.0210	0.0050	0.0110	0.0026	%wt
Manganese (Mn)	0.7840	0.0590	0.1084	0.0254	%wt
Nickel (Ni)	0.0280	0.0050	0.0098	0.0033	%wt
Copper (Cu)	0.0490	0.0080	0.0144	0.0048	%wt
Tin (Sn)	0.0160	0.0010	0.0045	0.0022	%wt
Vanadium (V)	0.0050	0.0010	0.0020	0.0006	%wt
Nitrogen (N)	0.0055	0.0012	0.0029	0.0006	%wt
Aluminium (Al) (Total)	0.0690	0.0130	0.0486	0.0066	%wt
Aluminium (Al) (Soluble)	0.0640	0.0120	0.0451	0.0061	%wt
Niobium (Nb)	0.0040	0.0010	0.0010	0.0001	%wt
Boron (B)	0.0005	0.0001	0.0001	0.0000	%wt
Titanium (Ti)	0.0710	0.0020	0.0498	0.0057	%wt
Chromium (Cr)	0.0320	0.0080	0.0170	0.0033	%wt
Titanium Excess (Ti*)	0.0329	-0.5881	0.0154	0.0185	
Ultimate Tensile Stregth (Rm)	344	268	303	9	N/mm^2
Proof Stress (Re)	236	109	173	13	N/mm^2
Elongation (A)	52	30	42	3	%
Strain Ratio (r)	3.51	1.09	2.36	0.27	
Strain Hardening Exponent (n)	0.256	0.193	0.231	0.008	

Inputs in italic are ones that differ to the Port Talbot data set.

It is important to note the differences between the data used to make the models. Whilst the process conditions themselves are of great importance, with the Zodiac process condition being considerably different to those of CAPL, the statistical values relating to the values is also significant. For example the properties recorded for the two data sets show some important differences. The ultimate tensile strength and proof stress values of the 3004/05 steels produced on Zodiac both have lower standard deviation values than their CAPL counterparts. The accuracy that the properties are recorded to also differs depending on which line they are produced on.

Models of the 3004/05 steels were produced using the same method detailed above, this time trained with data from the Zodiac line. In order to accurately compare the results of the new models with those of the DC05/06 steels only coils that had met specification were selected. This meant that there were 4267 coils with which to produce the model. This was divided into the same subsets as before (100 coils in the validation and training subsets); leaving considerably more coils in the modelling subset then had been used previously. In an attempt to reduce the complexity of the model the inputs were chosen using the selection criteria utilised before; only inputs that had a correlation coefficient of greater than 0.1 and those suggested by line specialists were selected. The outputs of these models are shown in Figures 4.17 to 4.21. Error lines showing ±5% have again been superimposed on to these results and statistical data about all the models is collated in table 4.6.

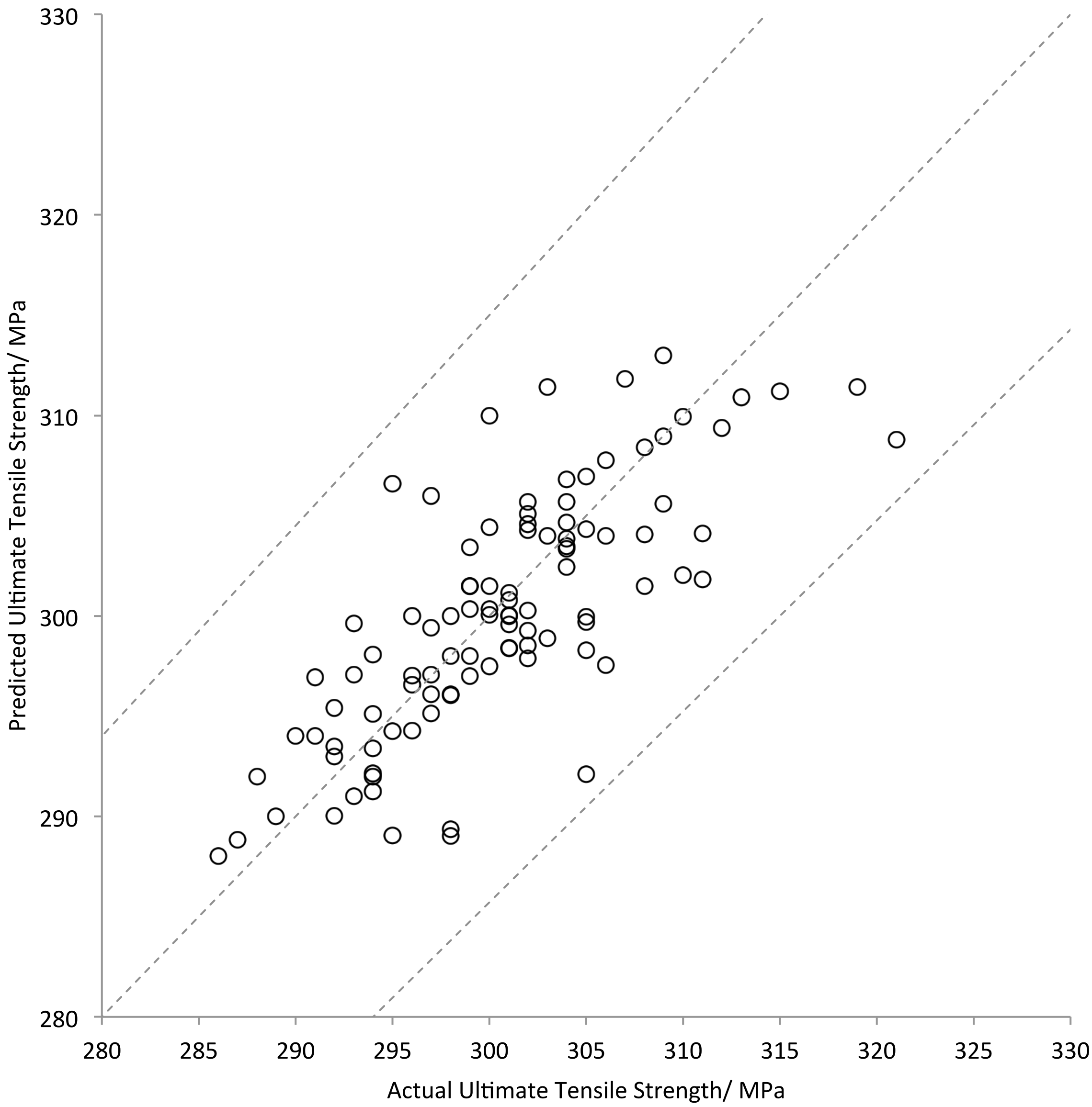


Figure 4.17: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for 3004/05 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 0.6560. The following inputs were chosen:

Physical: gauge, width, length and cold reduction

Zodiac: direct fire temperature, snout temperature, radiant tube furnace exit temperature, temper mill tension in and line speed

Hot Rolling: drop temperature, rougher temperature, and coiling temperature

Chemistry: Carbon, Silicon, Phosphorus, Manganese, Nickel, Vanadium, Titanium and Titanium excess

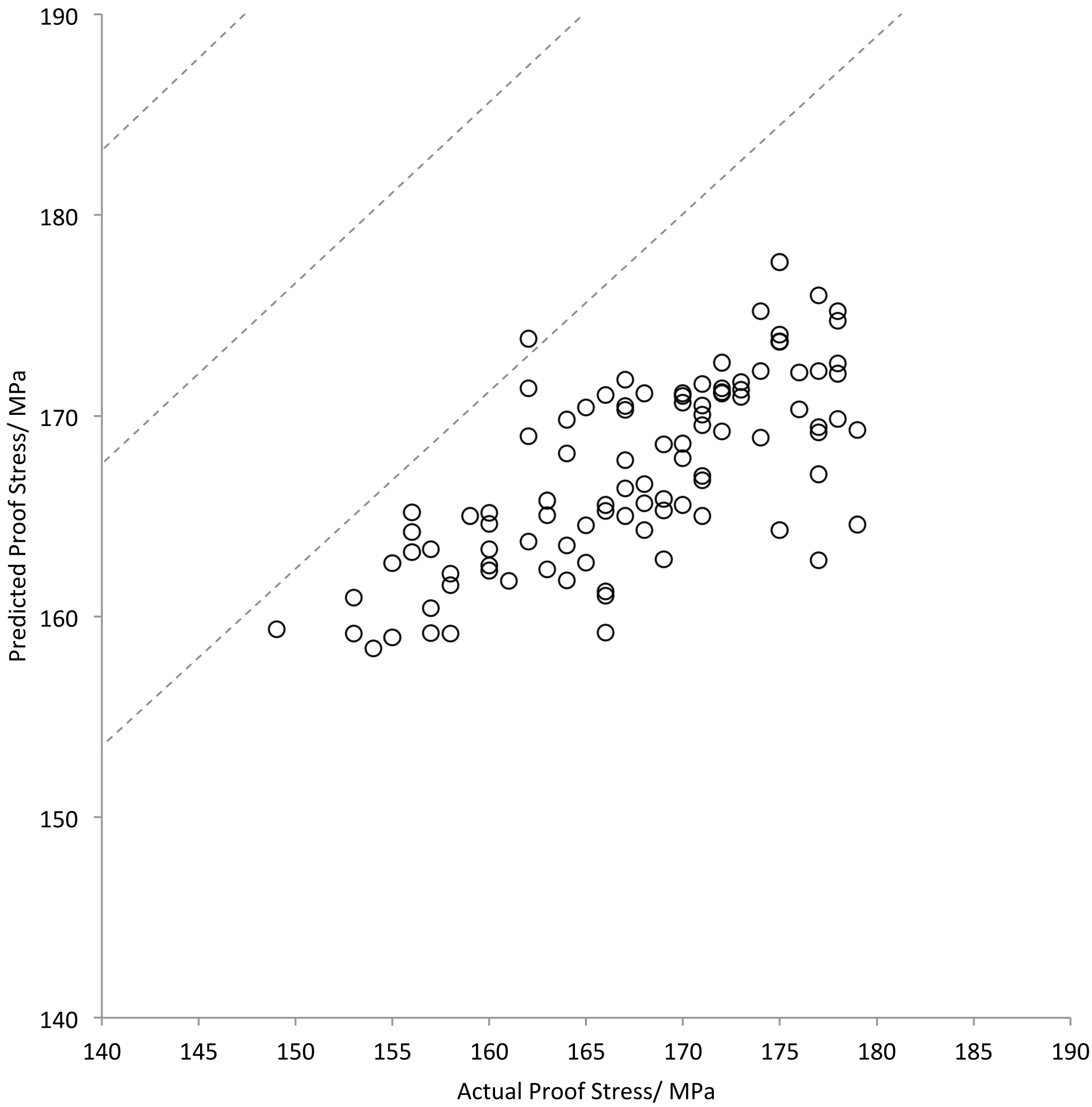


Figure 4.18: Actual proof stress values against proof stress values predicted by a generalised regression model for 3004/05 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the proof stress model was found to be 0.9749. The following inputs were chosen:

Physical: gauge, width and cold reduction

Zodiac: direct fire temperature, radiant tube furnace exit temperature, snout temperature, line speed, temper mill load, temper mill tension in and temper mill tension out

Hot Rolling: finishing temperature and coiling temperature

Chemistry: carbon, manganese and titanium excess

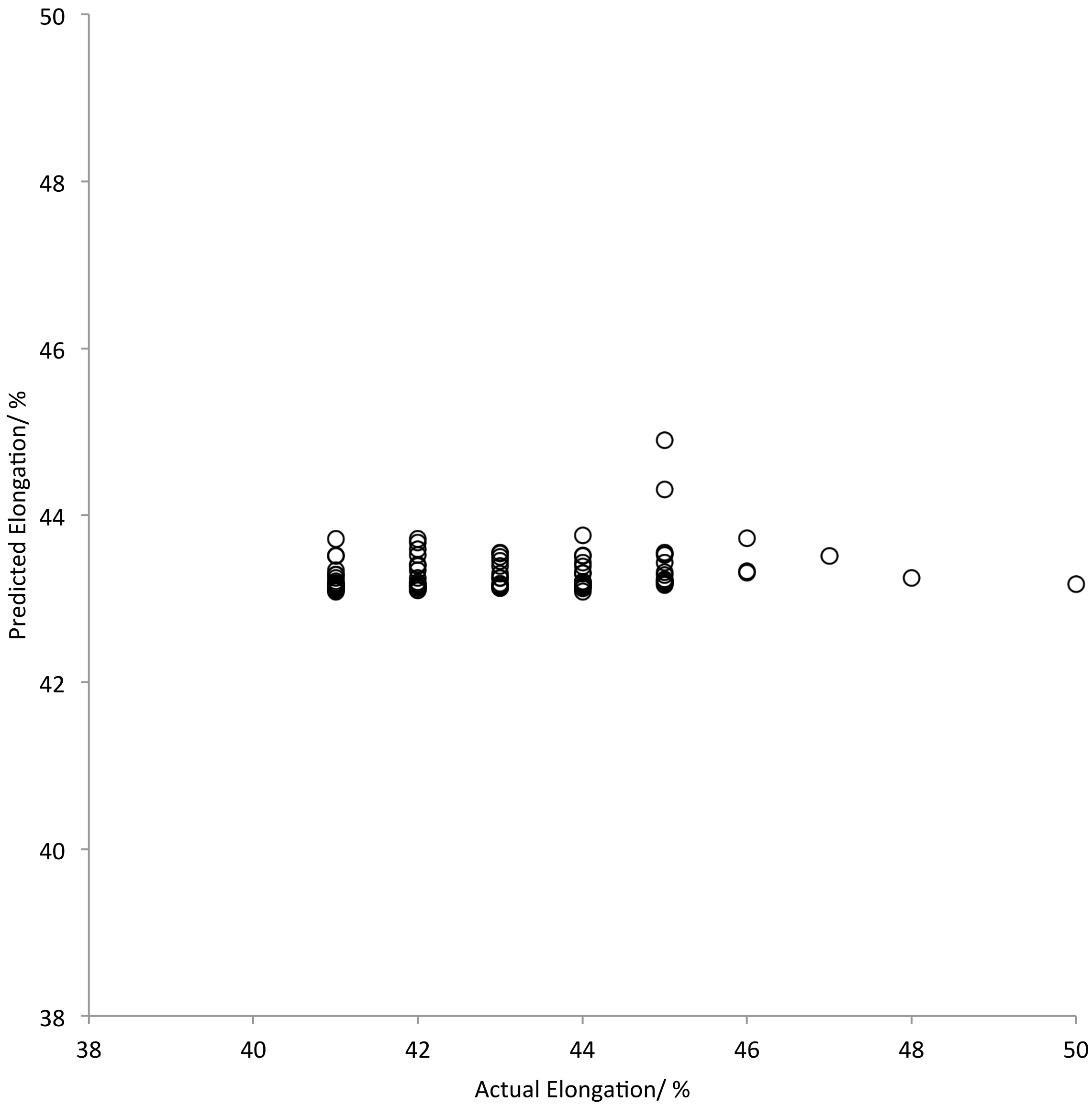


Figure 4.19: Actual elongation values against elongation values predicted by a generalised regression model for 3004/05 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the elongation model was found to be 1.0484. The following inputs were chosen:

Physical: gauge and cold reduction

Zodiac: radiant tube furnace exit temperature and line speed

Hot Rolling:

Chemistry: Carbon, Manganese and Titanium excess

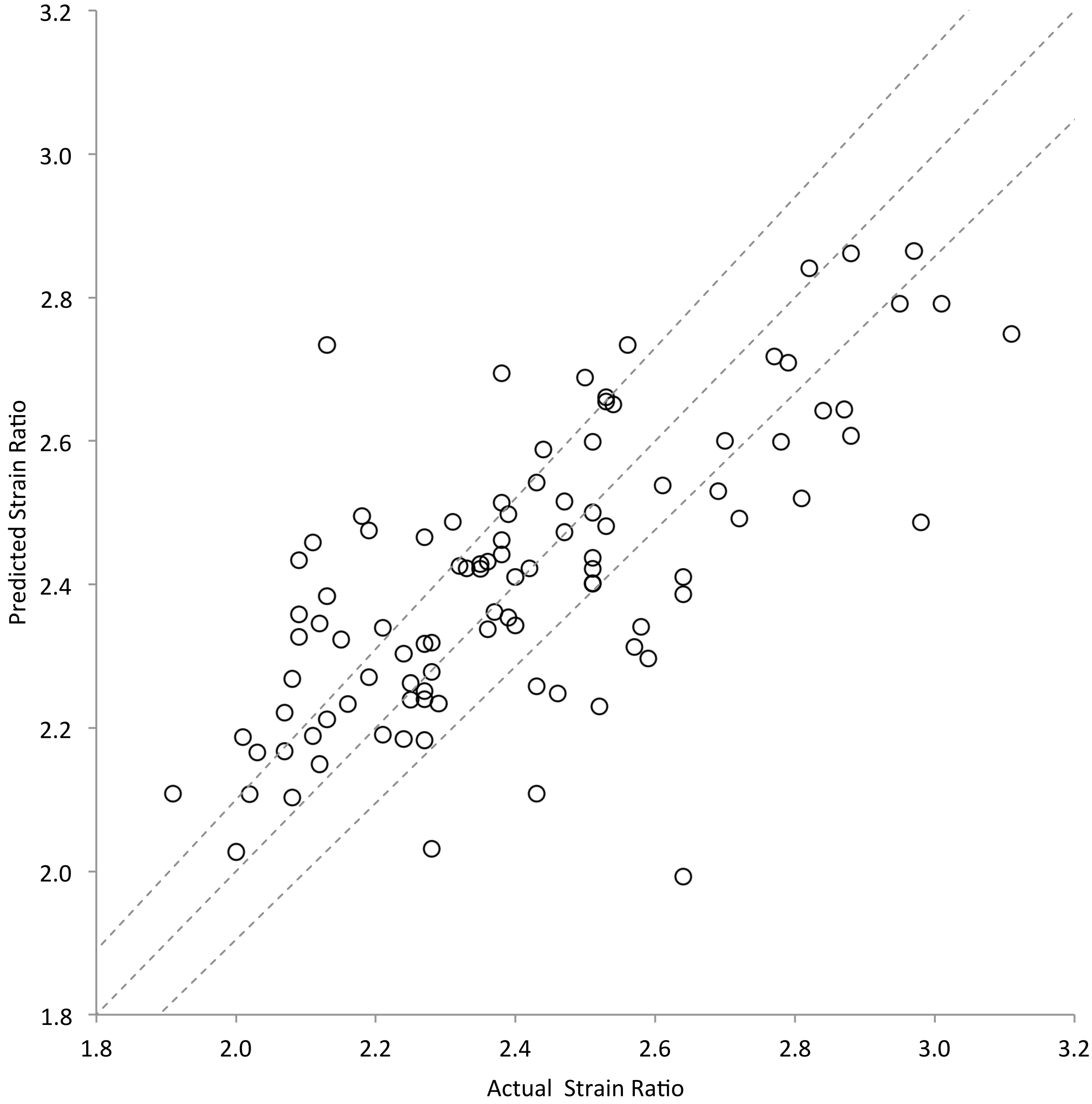


Figure 4.20: Actual strain ratio values against strain ratio values predicted by a generalised regression model for 3004/05 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 0.9383. The following inputs were chosen:

Physical:	gauge, width, length and cold reduction
Zodiac:	direct fire temperature, radiant tube furnace exit temperature, roll 30 temperature, water quench temperature, temper mil tension in, temper mill tension out and line speed
Hot Rolling:	drop temperature and finishing temperature
Chemistry:	carbon, phosphorus, manganese, vanadium, titanium, chromium, molybdenum and titanium excess

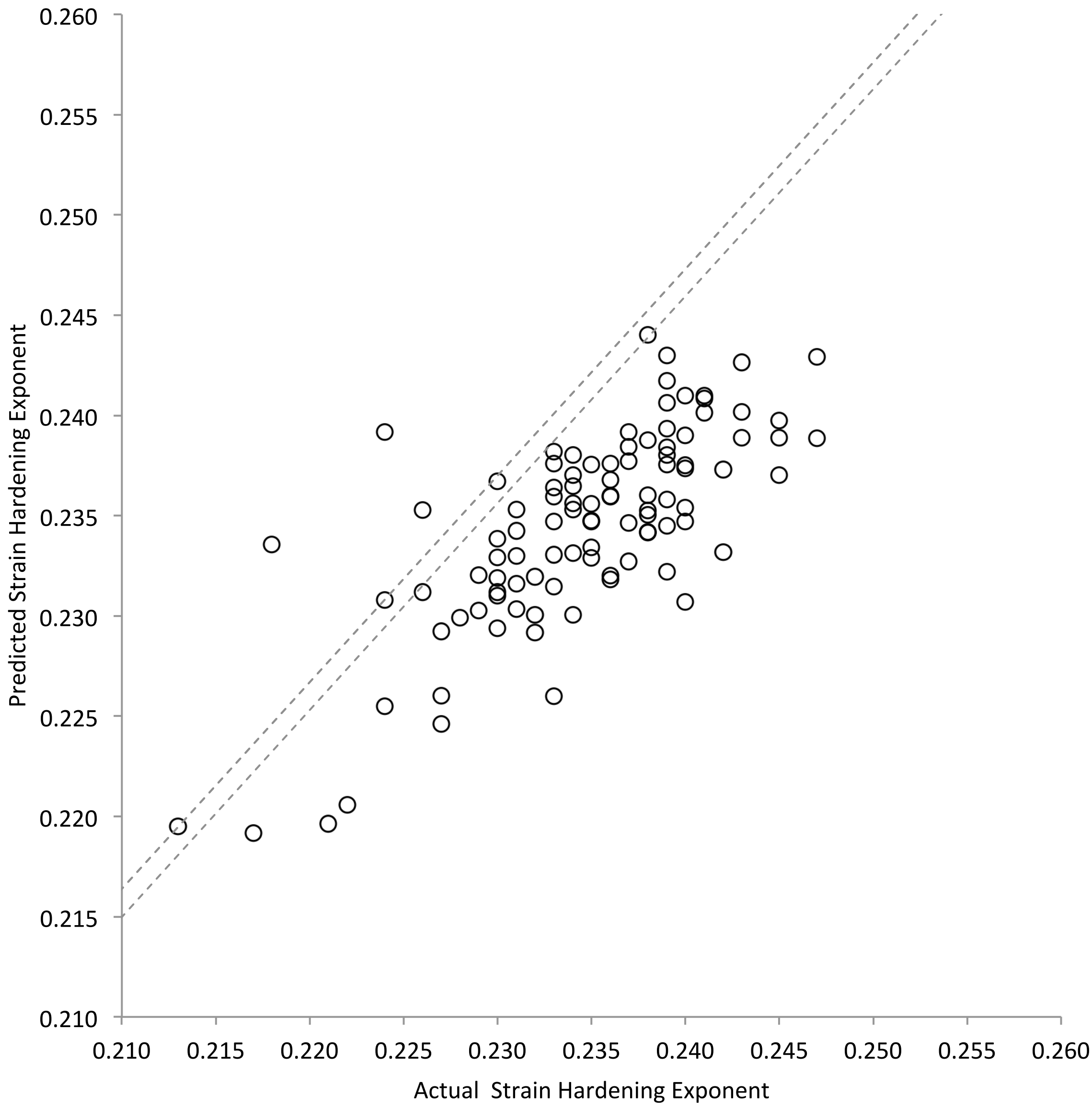


Figure 4.21: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for 3004/05 steels meeting specification using inputs chosen based on their correlation coefficients (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain hardening exponent model was found to be 0.4217. The following inputs were chosen:

Physical: cold reduction

Zodiac: radiant tube furnace start temperature, radiant tube furnace exit temperature, line speed, temper mill load and temper mill tension in

Hot Rolling:

Chemistry: carbon, manganese, nickel and titanium excess

Table 4.6: Statistical data produced from validation data set from a generalised regression model of 3004/05 steels meeting specification using inputs chosen based on their correlation coefficients

Property	**MSE**	**RMSE**	**MPE**	**R**
Ultimate tensile strength	19.0	4.4	1.08%	0.77
Proof stress	25.6	5.1	2.38%	0.71
Elongation	3.10	1.76	3.38%	0.20
Strain ratio	0.036	0.19	6.08%	0.69
Strain hardening exponent	0.00002	0.004	1.33%	0.75

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

The modelling technique produces two methods of assessing the success of its models. Firstly, and most obviously, the accuracy of any predicted results will ultimately determine how a model is judged. Three of the models were able to produce reasonably accurate predictions. The predictive errors are comparable to other predictive methods [60]. Predictions for these grades of steel were in general of a greater accuracy than the predictions of steels produced at Port Talbot. The models predicting the ultimate tensile strength and strain hardening exponent produced results that mainly fell within the 5% boundaries and a mean percentage error of almost 1%. The proof stress prediction, whilst not quite as accurate, again fell mainly within the superimposed limits. Whilst there were some outliers, the strain ratio predictions also showed a reasonable fit with the forty-five degree line. The reason for the increase in the predictive accuracy compared to other models is not easily explained. A simple explanation might look at the number of coils used to produce the models. One would assume that a greater amount of data would produce a model that was more accurate. While this was the case comparing the interstitial free steel models of steels produced on Zodiac and CAPL the models of DC01/03/04 steels had considerably more coils than either and did not produce models with a greater accuracy. This may be attributed to the relationships between the properties and process conditions of the interstitial free steels not being as complex as the other grades.

The discrepancy between these results and those relating to the Port Talbot steels needs some consideration. The inputs used to produce these models are different to the previous models; so this may be one explanation. The microstructure of the steel is altered by the heating regime that coil undergoes. The new models have more references to these heating regimes, particularly the cooling phases, and may therefore produce a better estimation of them. An inspection of the inputs selected for the two sets of models suggests that this may be some truth to this assumption as some models (proof stress, strain ratio and strain hardening exponent) have more temperatures as inputs for the Zodiac steels than the Port Talbot alternatives. Looking further at the strain hardening exponent inputs suggests a flaw in this though, as the temperature inputs to the Zodiac model are those at the start and finish of the radiant tube section. The radiant tube furnace temperature is one of the conditions that can be chosen as an input to any of the CAPL models. However, it was not chosen as one of the inputs to the CAPL strain hardening exponent. This suggests that something in the Zodiac data set made the relationship between temperature and strain hardening exponent stronger and easier for the model to pick up. A final, and more controversial, option might be that the measurements for the Zodiac coils (both process conditions and properties) are of a higher standard than those from CAPL, resulting in a better data set to base models on. This is a common problem with models of this type leading to the expression 'garbage in, garbage out' (Fuechsel, cited in [62]).

The elongation model produced interesting results. The thin spread of results at a value of around 43% suggests that this approach is not suitable to model this property. By investigating the data used to create the model it soon became apparent as to the main reason behind these poor predictions. The elongation value is recorded as an integer value. The actual measured property varies between 41% and 48%. The sort range and limited resolution meant that there was little scope for the modelling process to distinguish between the different values. This assumption is upheld by the optimised value being quite high. Generalised regression networks with a higher spread value make greater use of old entries that don't match the new entry closely. In this example the variation in the associated outputs is likely to be large due to the way the elongation is recorded. Process conditions relating to an actual elongation of 41% will have no values below it to call upon (due to the range of the data) and the large spread will mean that many of the large elongation values are used in the prediction. Likewise at the top end of the range the small values will be used in the prediction. The overall effect of this is that all predicted values move towards a central point.

4.7. Conclusions

In this chapter generalised regression models were developed to predict the properties of continuous annealed steels based on processing conditions and the steel's chemistry. Models were produced to predict the ultimate tensile strength, proof stress, elongation, strain ratio and strain hardening exponent. Using all available inputs, models of DC05/06 steels were able to outperform the basic linear regression models of the same grades. Later models using only inputs selected based on their correlation to the output properties and expert knowledge were not able to match these results but proved again to be more accurate than the basic regression approach.

The modelling approach was also shown to have limited success predicting the properties of different grades of steel produced on the same line, DC01/03/04. A much larger data set failed to deliver increases in the predictive accuracy yet still provided reasonable predictions for some of the properties. The modelling work was extended further to cover steels produced on a different annealing line. The accuracy of these models was greater than any previously produced model, with all models producing a mean percentage error of 6% or less. Predictions of the elongation value produced a similar plateau as seen with other grade which may relate to the recording of the value and the narrow range of data.

These findings suggest that generalised regression network based models are a suitable non-linear method for predicting many of the properties of annealed steels for the grades under consideration. Reducing the number of inputs to such models has an adverse effect on the predictive accuracy, but training errors suggest that this can be improved upon. While the predictive method used was non-linear the input selection is still based on a linear approach. In order to unlock the full potential of the generalised regression network a more suitable input selection method needs to be found which takes into account the non-linear relationships that exist.

CHAPTER 5 – IMPROVING THE PREDICTIVE ACCURACY USING A GENETIC ALGORITHM

5.1. Introduction

The previous chapter gave details on how generalised regression networks were chosen to fulfil the task of predicting the properties of continuous annealed steels and how this method was implemented. Models were produced using the full set of inputs available or a selection of inputs based on their correlation with the output properties. This reduction in the number of inputs reduced the computing power required to run the models (models of grades using several thousand coils to populate them took longer to run). The reduction in the number of inputs to the models may also help increase the transparency of any model produced; the important inputs are easier to identify as they are the ones that are selected.

The models produced in the previous chapter relied on the linear correlation between the input processes and output properties as the main input selection criteria. In addition to this expert knowledge was employed in an attempt to pick up on some of the subtleties of the continuous annealing process. Whilst this method was able to produce satisfactory results for some of the grades and properties under investigation it was not felt that it was optimal. The main concern was that the linear relationship between inputs and properties was used when in fact many of the relationships that exist in the process are likely to be of a higher order.

With this in mind, a method of optimising the selection method was sought. Of particular importance was the need for this method to be efficient. Trying every combination of the forty available input conditions would require two to the power of forty iterations to be carried out to produce just one model. With the time and computing power available this would not be practicable, nor would a method requiring a significantly large number of iterations.

5.2. Genetic Algorithm Implementation

The continuous annealing process involves several processes that require careful control in order to achieve the desired mechanical properties. Each of these properties represents a possible input to any model of the process. Strip steel undergoing continuous annealing will also have been subject to several other thermo-mechanical processes, these processes too require control and may also be considered as model inputs. One thing to consider, which is seen to have an effect on the final properties of the strip, is its physical dimensions. Though, for example, the thickness of the strip will not necessarily have an impact on the properties itself, it will determine the line speed and hence the soak time. The amount of cold reduction will also be important. Clearly, this leads to a choice of several possible inputs. Choosing the right combination of these inputs is a critical factor to the success of any prediction model; too few will lead to poor accuracy, while too many will overcomplicate the model, possibly leading to long run times.

It was with this in mind that a method of optimising the inputs used by each model was investigated. In the previous chapter only the spread value was optimised. As this was a single factor the optimisation was simple. The basic approach relied on creating a model with an initial spread estimate, analysing the error and changing the spread value accordingly. If a similar approach could be employed to optimise the model inputs, changing the trial input set based on the associated error, then this would negate the need to try all possible input combinations. Using a genetic algorithm would produce a similar method, whereby the best sets of inputs from several trial sets are combined to produce new sets to trial.

In order to be used with the generalised regression network function, coil information had to be stored in columns. This meant that each row of the data set related to a process condition or property. The correlation based input selection method called on process conditions by means of a string of numbers relating to the rows containing those conditions. For example the string {3,6,18,27,31} would call the inputs width, radiant tube furnace temperature, percentage cold reduction, sulphur and copper as these were stored in the corresponding rows. In order to use a genetic algorithm to optimise the inputs, a method of representing these as a binary string was needed. However, so that much of the original programming could still be used, the inputs would still need to be represented in the form detailed above.

For the purpose of the genetic algorithm, an input set was represented by a binary string of 40 bits. Each bit represented a single process condition and its position in the string detailed which process this was, using the same form as above. Bits that had a value of one represented processes that were being used and bits with a value of zero represented those not being used. In order to convert from this form into one compatible with the previous work, a simple routine was devised. Each bit was multiplied by its position in the string. This resulted in processes not in use having a value of zero and those in use having a value representing their row. By removing all the zero values from this string, the input set could then be used with previous programming. A similar function was programmed that converted a set of input rows into a 40 bit binary string.

With the necessary conversion methods developed, the genetic algorithm could be now be implemented. An initial population of twenty five input sets was created. Of these initial input sets, one represented all inputs being used, one with all even inputs used and one with all uneven inputs used. The ability to include an input set from previous testing was also included. If this was not present, a set was created using the linear correlation criteria detailed in the previous chapter. The remaining twenty one sets were created randomly. Each input set was then used to create a network, which was then used to simulate the properties of the test data. The mean square error from each network was then calculated. The networks were then ranked according to their associated errors. The input sets used to create the networks producing the four lowest errors were carried forward to create a new population for the next iteration.

Using these input sets, the new population was constructed in the following ways:

- The input set associated with the lowest mean square error was carried forward in its original state.
- Six new inputs sets were created by randomly splitting and then combining the four selected inputs sets, i.e. first with second, first with third, first with fourth, second with third, second with fourth and third with fourth.
- An additional two input sets were mutations of the input set associated with the lowest error.

The combination and mutation of input sets centres on splitting the input sets from the previous iteration at a random point along their length. For combinations the split is made and then the two halves of different input sets are joined to form two new sets. For example; two input sets (A and B) are to be combined. The split has been determined to occur after the 26th bit. The split occurs leaving four partial inputs sets (A_1, A_2, B_1 and B_2), with those designated '1' being of length 26 and those designated '2' being of length 14. A_1 is combined with B_2 and B_1 combined with A_2 to give two new inputs sets (C and D) each of length 40. The mutation occurs in a similar way. This time only one input set is split. The beginning and end bits of the new input sets are made up of a partial input set of randomly determined bits the length of the missing half.

So that a population of twenty-five inputs sets was available for the next iteration, the remaining sixteen sets were created randomly. In order to improve the efficiency of the algorithm, and to make sure that the widest range of possible inputs sets was considered, a routine was included that checked none of the newly created input sets had been analysed previously. If a duplicated input set was found, it was simply replaced by a new randomly created one. The routine was then repeated using the new population of twenty five inputs sets.

5.3. Combining Spread Optimisation and a Genetic Algorithm

The use of a genetic algorithm to optimise the inputs of a generalised regression network introduces difficulties in optimising the spread value of the network. With the basic modelling approach described in chapter four, the spread is optimised for a single set of inputs. The few minutes it took to train networks in this manner was suitable for this training method. When the genetic algorithm is introduced, the number of times this optimisation is required increases dramatically for each input set and number of iterations it needs to be run. An alternative approach may be to optimise the spread value at the end of the input optimisation process only. This approach would require a spread value to be present at the beginning of the input optimisation process; how this is found will impact on the remainder of the process.

The different approaches to integrating the spread optimisation into the new training regime were both investigated. Choosing when to optimise this value was likely to be a choice between a higher accuracy of the final network and the speed of the training routine. The first approach looked into creating a training routine which periodically altered the spread value in an attempt to decrease training time. This would then be compared to the second approach, where the spread was optimised for each input set, to see what the effect was on the accuracy of the complete training routine. Investigating the properties of one grade of steel carried out the comparison, this being the 3004/05 steels produced on Zodiac; chosen due to the accuracy of the previous models of these properties.

5.3.1. Input Optimisation Using a Constant Spread Value

In order to produce models for each input set and iteration, the first approach required that an estimate of the best input set was provided to find an initial spread value. If a previous input set was provided then this would be used with the optimisation routine detailed previously. With no input set provided, the training routine found an input set using the correlation method outlined previously and used these. With the spread value found, the genetic algorithm could be implemented. In the same way as had been done with previous models, modelling, training and validation data sets were formed to develop the model. A network was created for each input set using the initial spread value. Predictions based on the training data were produced for each network and the mean square error found.

At the end of the first iteration the lowest error using the training data set was recorded. Using the input set associated with this value, the error for the validation data set was also found. These errors along with the associated input set were stored. The new input sets developed by the genetic algorithm were then used for the next iteration. The lowest error for the training data was again found. This was compared to the error achieved in the previous iteration, if it was no lower than the previous step a count was started. A lower error resulted in the error for the validation set being calculated and the value of the count being reset. If the validation error was found to be lower than the previously recorded value then the new value and associated input set replaced the stored value. The routine would then continue in a similar manner with the count increasing if the error from training data did not change.

When the count reached ten the routine stopped and the last recorded input set (the one associated with the lowest validation data error) was used to calculate a new spread value. The training routine was then repeated using networks with the new spread value until the count once again reached ten. At this point a final spread value was calculated and a final network created using this and the appropriate input set. A simplified diagram of this training routine is shown in Figure 5.1.

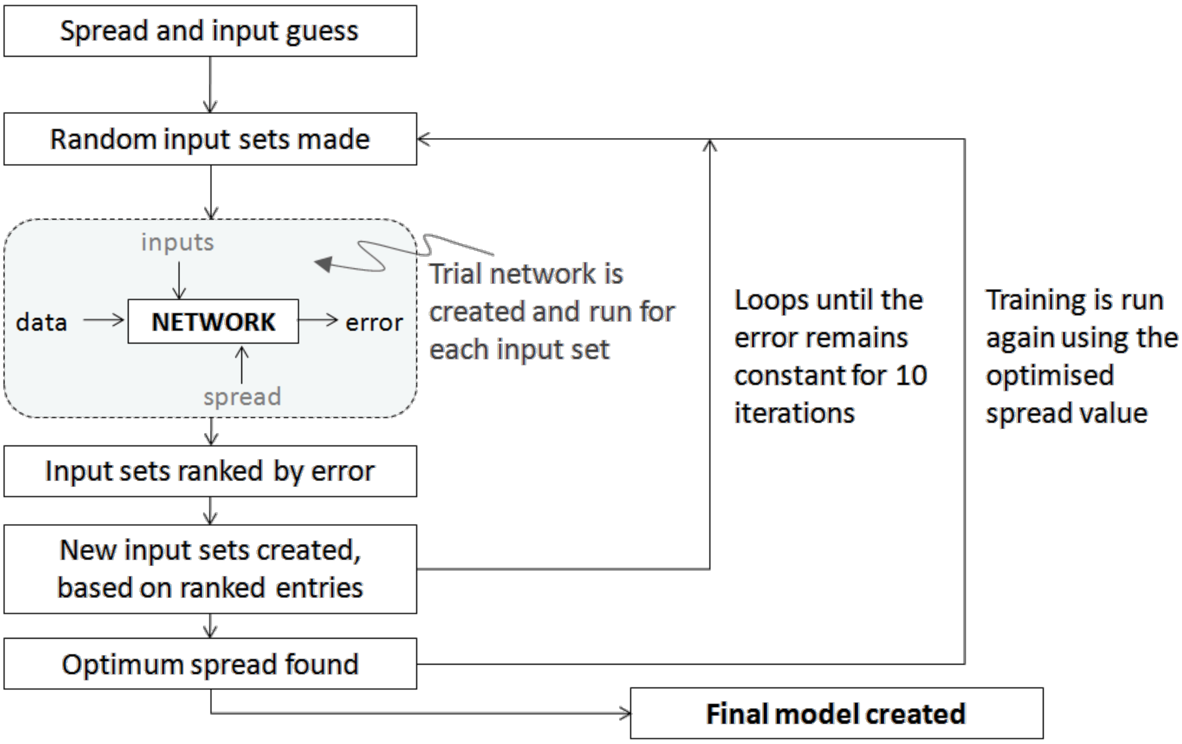


Figure 5.1: Simplified flow diagram of the model training routine using a constant spread value in the genetic algorithm

Using the training method outlined above, models were developed to predict the properties of 3004/05 steels produced on Zodiac. The predictions from these models are shown in Figures 5.2 to 5.6. Statistical data about these results is given in Table 5.1. As before, lines representing where the predicted value equals the actual value, as well as ±5% error lines have been superimposed onto these results.

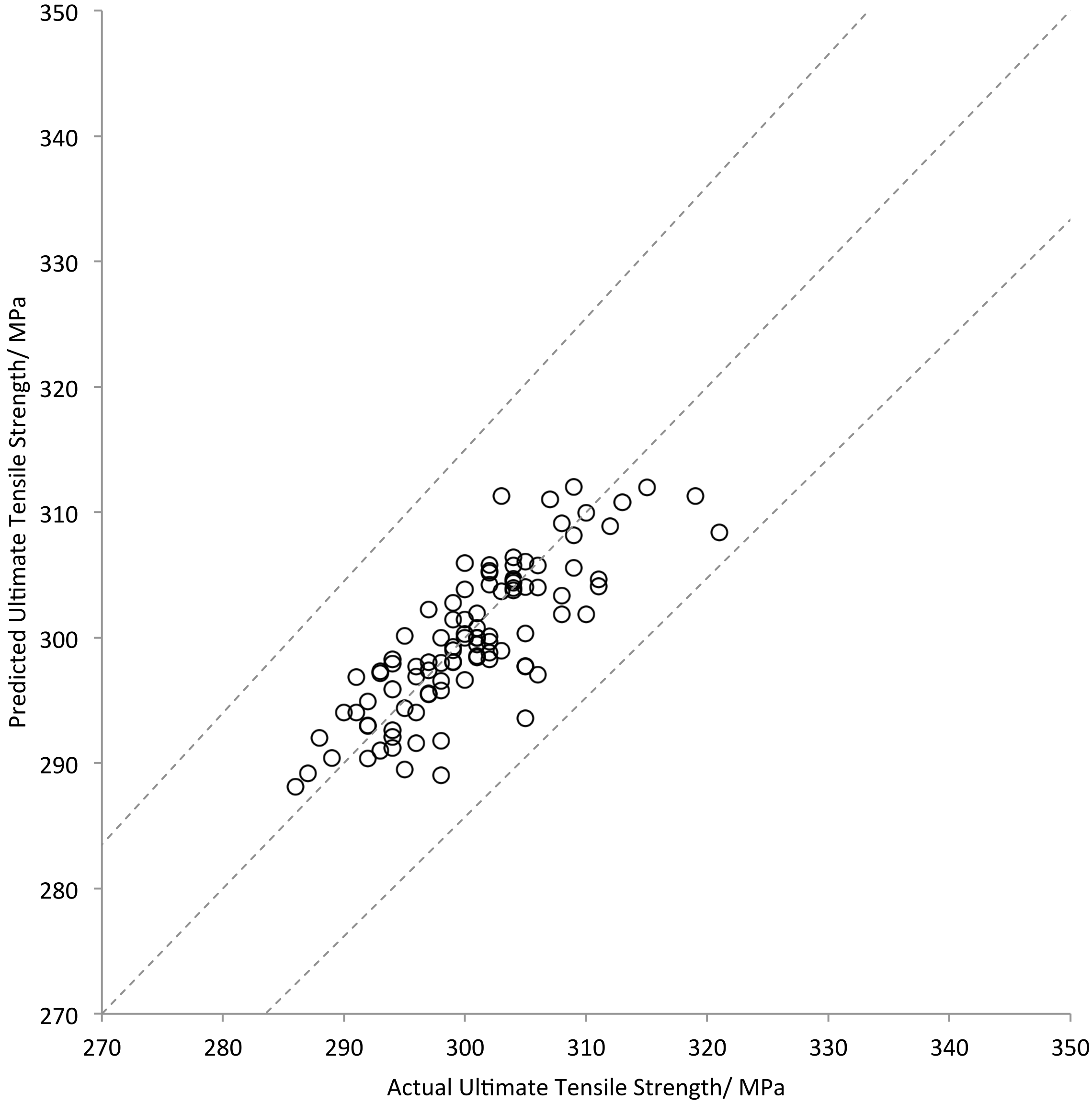


Figure 5.2: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 0.6560.

The following inputs were chosen:

Physical: weight and cold reduction
Zodiac: direct fire temperature, radiant tube furnace exit temperature, pot temperature and roll 30 temperature
Hot Rolling: drop temperature and rougher temperature
Chemistry: manganese, nickel, nitrogen, aluminium (total), niobium, boron, titanium, molybdenum and titanium excess

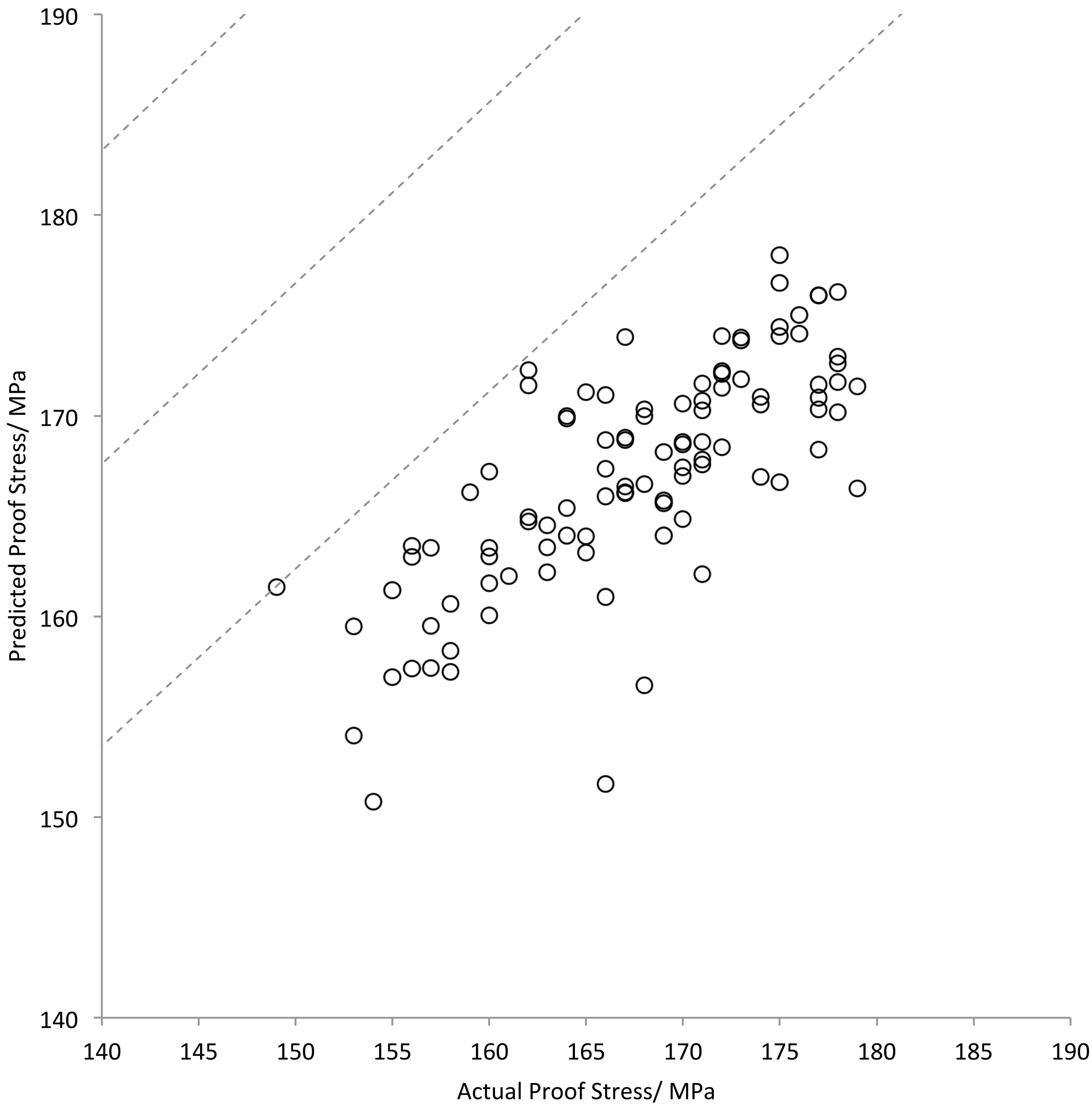


Figure 5.3: Actual proof stress values against proof stress values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the proof stress model was found to be 0.9770. The following inputs were chosen:

Physical: gauge and width

Zodiac: direct fire temperature, radiant tube furnace start temperature, radiant tube furnace exit, roll 30 temperature, temper mill load, temper mill tension in and line speed

Hot Rolling: rougher temperature

Chemistry: carbon, silicon, sulphur, nickel, tin, vanadium, aluminium (soluble), niobium, molybdenum, arsenic and titanium excess

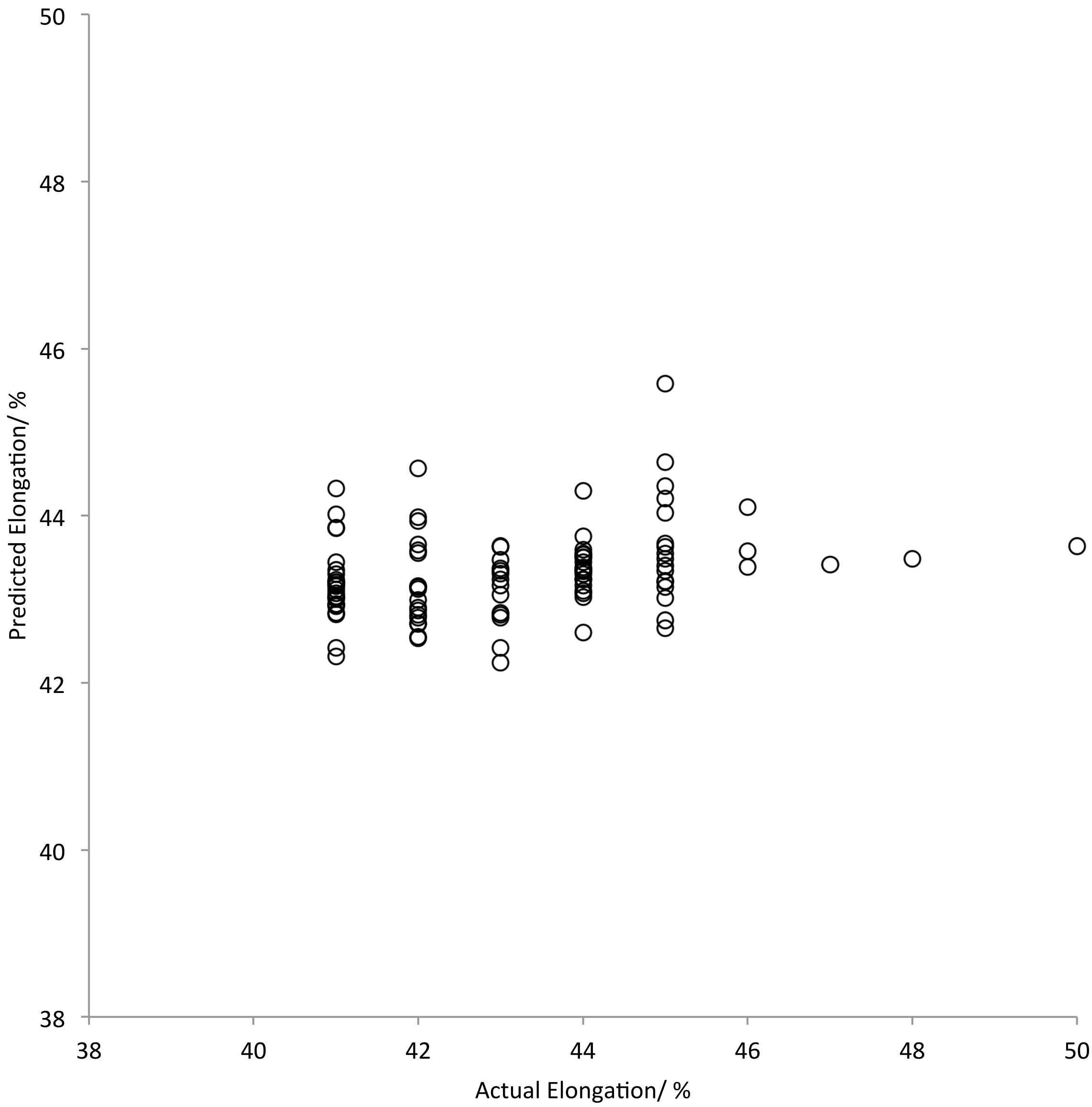


Figure 5.4: Actual elongation values against elongation values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the elongation model was found to be 0.9992. The following inputs were chosen:

Physical:	width, length and weight
Zodiac:	snout temperature, temper mill tension in, temper mill tension out and line speed
Hot Rolling:	finishing temperature
Chemistry:	carbon, tin, aluminium (total), aluminium (soluble), niobium, boron, titanium and titanium excess

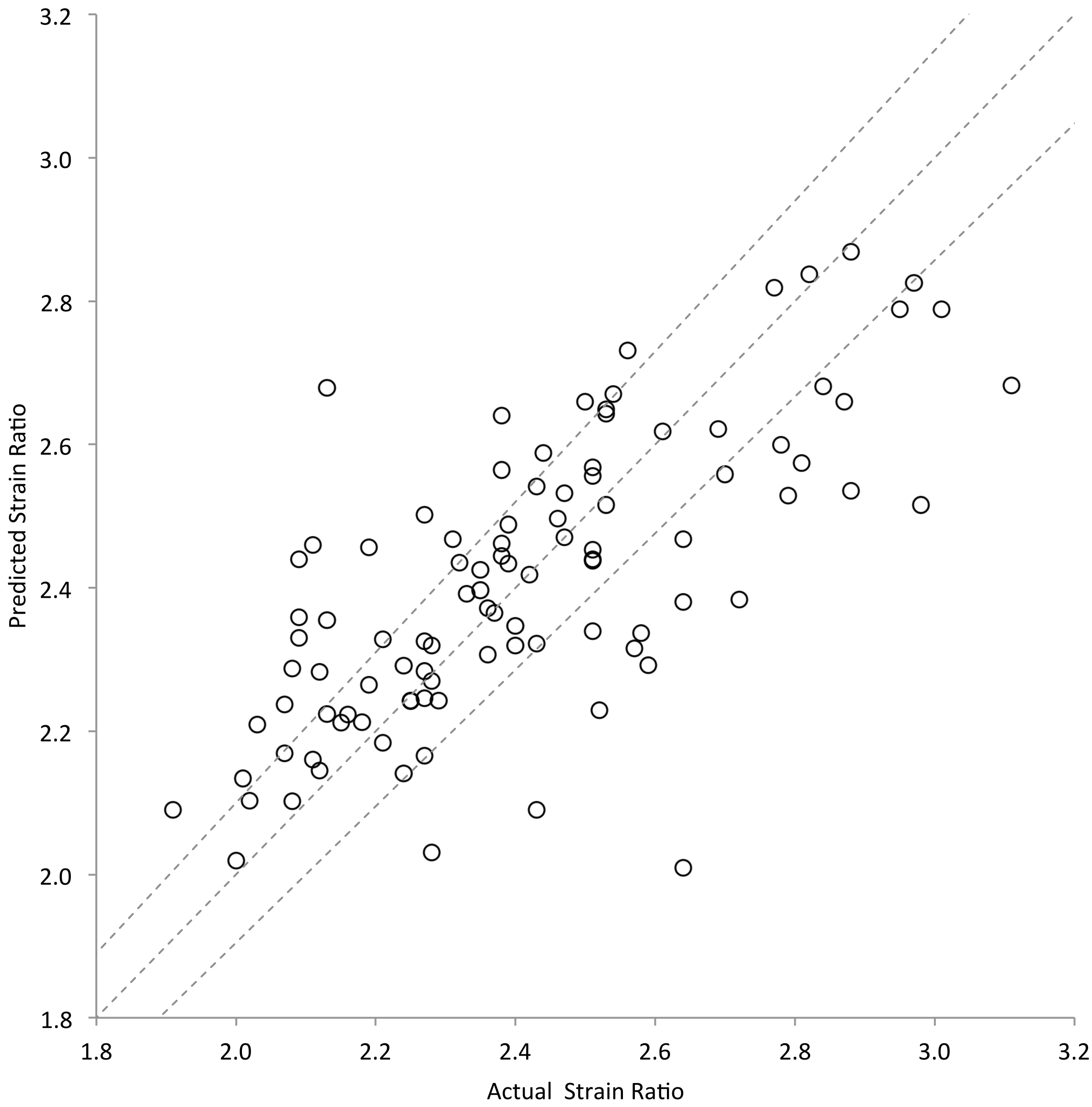


Figure 5.5: Actual strain ratio values against strain ratio values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 0.9784. The following inputs were chosen:

Physical:	gauge and cold reduction
Zodiac:	direct fire temperature, radiant tube furnace start temperature, radiant tube furnace exit temperature, pot temperature, roll 30 temperature water quench temperature, line speed, temper mill tension in and coating weight
Hot Rolling:	drop temperature, rougher temperature and finishing temperature
Chemistry:	carbon, silicon, phosphorus, manganese, tin, aluminium (total) niobium, chromium and titanium excess

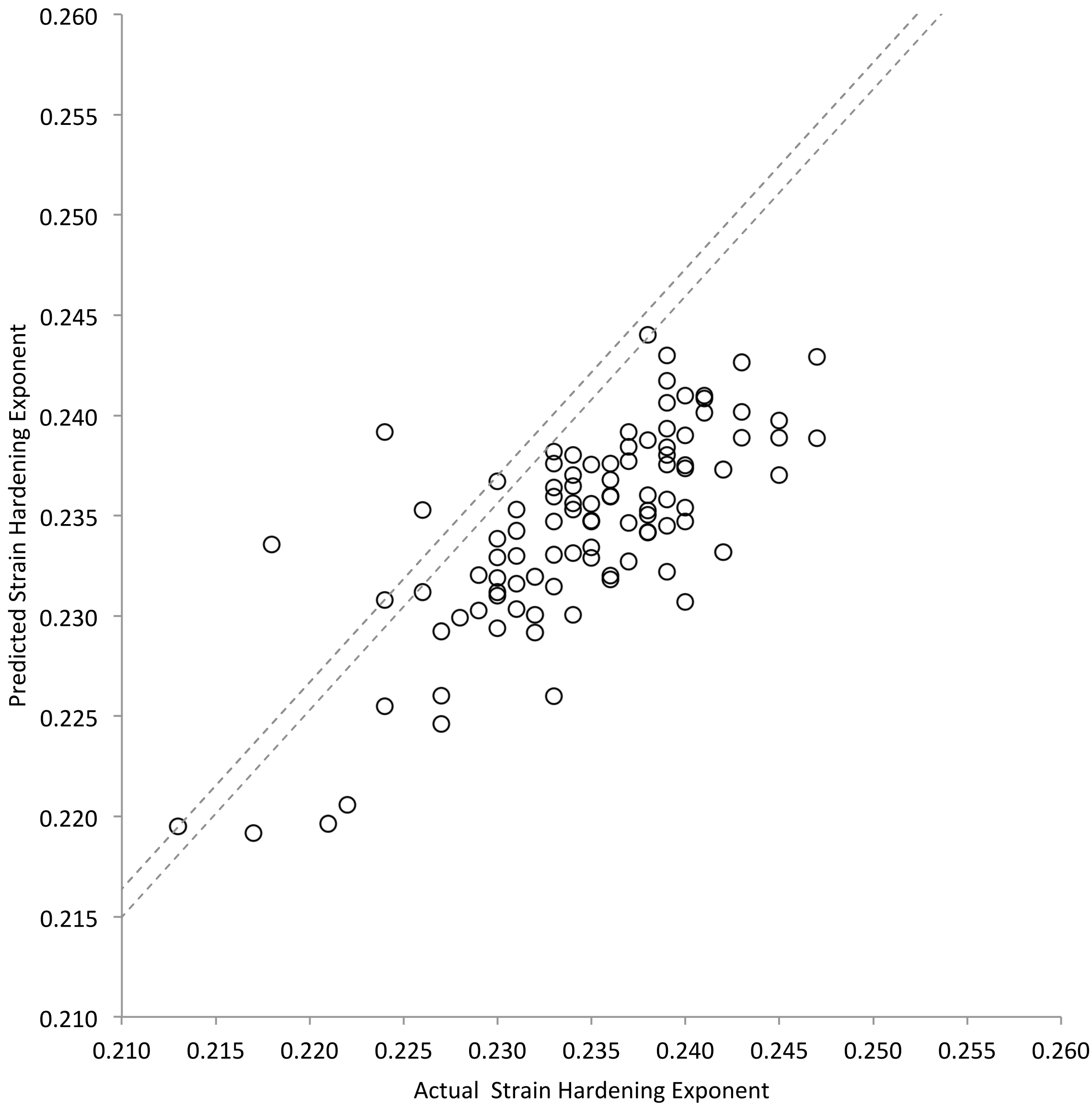


Figure 5.6: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain hardening exponent model was found to be 0.4217. The following inputs were chosen:

Physical: cold reduction

Zodiac: radiant tube furnace start temperature, radiant tube furnace exit temperature, temper mill load, temper mill tension in and line speed

Hot Rolling:

Chemistry: carbon, manganese, nickel and titanium excess

Table 5.1: Statistical data produced from validation data set from a generalised regression model of 3004/05 steels meeting specification trained using a genetic algorithm and constant spread value

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	15.5	3.9	0.99%	0.81
Proof stress	22.8	4.8	2.12%	0.75
Elongation	2.95	1.72	3.23%	0.29
Strain ratio	0.035	0.19	5.75%	0.71
Strain hardening exponent	0.00002	0.004	1.33%	0.75

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Using a genetic algorithm to select which process conditions should be inputs to the generalised regression networks it was possible to reduce the predictive error for all but one of properties under investigation. When compared to the best previous results, found using the generalised regression network with all possible inputs, the reductions in the root mean square error were as follows: ultimate tensile strength 9.5%, proof stress 5.7%, elongation 2.4%, strain ratio 2.7% and strain hardening exponent 0.0% As well as the reduction in error models exhibited an increase in the correlation value, showing a better agreement between the predicted and actual results.

Several key observations can be made with regards to difference between this approach and the previous one, as well as the training method in general. The first of these is the lack of change in the predictive error from the strain hardening model. This lack of improvement may be related to correlation between the process conditions and the properties. A stronger linear relationship was observed between certain process conditions and the strain hardening exponent than the other properties. One may therefore assume that the original linear correlation based inputs model was closer to being optimal for this property than for the other two, meaning that there was less scope for improvement.

The ultimate tensile strength model was found to have the same spread value as the correlation based input selection model, even though the inputs chosen were different. This relates to mechanisms within the training program to prevent the model overfitting to the training data. For the initial training period the test input sets are used in conjunction with a spread value optimised using linear correlation based inputs. Models producing a lower error but using a different input set during this part of the training all have the same spread value. The inputs and spread producing the lowest training and validation error at all stages of the process are recorded. When a new spread value is calculated (after the training error has remained constant for ten iterations) the best input set from the first stage of the training process is used. The training error is used to optimise this value; so while the new spread value may reduce this error its effect on the validation error may not be the same. If the validation error fails to better the previously recorded values during the next stage of the training process the new spread value will not be retained, the training will output the spread value and input set matching the lowest concurrent training and validation errors.

As well as assessing the models based on the error values they produce, the inputs used to produce these predictions can also be analysed. If the inputs selected match some of these known relationships, then one may assume that the model is picking up on the complex relationships that exist in the annealing process. Ferrite grain size refinement is a simple method of increasing the strength of steel. Results from other researchers suggest that this is influenced by the amount of cold reduction employed, the annealing temperature and the annealing time [19]. These process conditions have been chosen as inputs to the two strength models. The steel's chemistry can also play a major part in its final properties. There are two common strengthening methods that can be employed, these being solid solution strengthening (normally related to the levels of carbon, phosphorus, manganese etc) and precipitation strengthening (normally related to the levels of vanadium, titanium, niobium etc)[5, 26, 32]. Though these methods may not be associated with the type of steel under investigation in this work it is important to note that some of the factors relating to them have been selected as inputs to the models relating to the steel's strength.

The relationships that exist between processing conditions and the formability of steel is another area that has seen a lot of research and so can be used to identify if the modelling process reflects the actual mechanisms for these properties. The strain ratio relates to the texture of the steel's microstructure. This is developed during recrystallization. The rate of recrystallization can be controlled by several factors, but the key ones are the soak temperature, amount of cold reduction and soak time [5, 32]. The amount of cold reduction and several temperatures from the annealing furnace are present as inputs to the strain ratio model. Though the soak time is not an input available for the model to select it can be deduced using the line speed, another one of the inputs selected.

The strain ratio can be related to some of the hot rolling process conditions. The coiling temperature is normally quoted as one of these factors as it is required to be high for continuous annealed steels to aid precipitate coarsening [5]. While this measurement has not been selected other similar ones have. A lower drop temperature is required continuous annealed steels as this prevents some of the precipitates from dissolving during the reheat phase and thus helps coarsen them [32]. Again, this is one of the inputs chosen.

Finally, there are certain alloying additions that are chosen due to their influence on the strain ratio. Excessive levels of carbon are avoided in coils that are continuously annealed due to their adverse effects at the higher annealing temperatures and its effect on texture development as an interstitial atom. Similarly, free nitrogen in the coil retards recrystallization and reduces the final properties. In order to overcome these difficulties titanium and niobium are added to combine with the carbon and nitrogen, leaving interstitial free steel in which the required textures can develop [32]. Levels of carbon and niobium were selected as model inputs. The titanium level is represented by the titanium excess value.

The training process has been shown to select inputs which relate to known relationships that affect the final mechanical properties of continuous annealed steels. Though not all of these relationships are associated with the steels under investigation it is important to consider them as known metallurgical principles. This has shown that the modelling process is capable of detecting some of the relationships that are involved in the annealing process.

5.3.2. Spread Optimisation for Each Input Set

The second approach to combine the spread calculation and genetic algorithm was based on calculating a spread value for every input set. The previous approach required that the spread optimisation only be carried out at three stages; the new approach would require it to be carried out twenty-five times for each iteration. To account for the extra time that this would take, the number of loops the training routine had to complete was altered and an early stopping method was introduced. These changes also reflected observations made whilst using the alternative approach.

As this new approach did not require a spread value to be found at the start of the routine, there was no longer a requirement to find an initial input set using the correlation method if a previous set was not provided. Networks were created for each input set with the spread value being found using the *fminsearch* function as described previously. The mean square error between the training data and the network predictions was then calculated. The network associated with the lowest error was then used to predict the properties of the validation data set. The error from this prediction and the associated input set was recorded. New inputs were then created using the genetic algorithm methodology detailed above. These were used in the next iteration.

The lowest error from the training data was found again. This was compared to the previously recorded training data error. If it was no lower than the previous iteration then two counts were started. The first of these counted the number of times the training data error remained the same, the second counted the lack of change in the validation data error. This second count related to the early stopping mechanism. A lower training data error resulted in predictions from the validation set being calculated and the training data count being reset. If the validation error was found to be lower than the previously recorded value, then the new value and associated input set replaced the stored value and the validation count was also reset. The routine would then continue in a similar manner with both counts increasing if the error from training data did not change. If there is a change in the validation error but the training error remains constant, then only the validation count increases.

As it was hoped that calculating the spread value for each input set would result in predictions of a greater accuracy, the routine continued until the count reached a value of only five. At this point the training was completed and a final network was created using the last recorded input set (the one associated with the lowest validation data error) and the associated optimised spread value. When using the alternative method it was observed that the validation error would remain constant for several iterations while the training error continued to decrease. The final validation error would be the same even though the extra iterations had taken place. For this reason an early stopping mechanism was introduced. If the validation data count reached twenty then the training finished, regardless of the training count value. A diagram of the training routine is shown in Figure 5.7.

Using the training method outlined above, models were developed to predict the properties of 3004/05 steels produced on Zodiac. The predictions from these models are shown in Figures 5.8 to 5.12. Statistical data about these results is given in Table 5.2. As before, lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results.

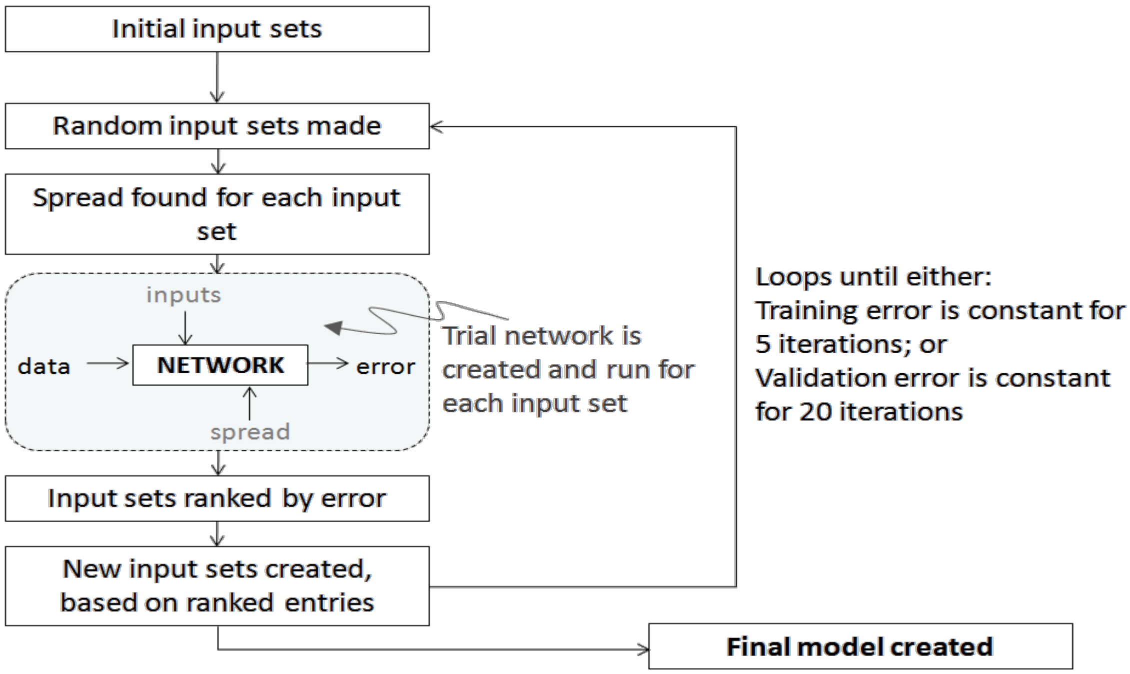


Figure 5.7: Simplified flow diagram of the model training routine using different spread values in the genetic algorithm

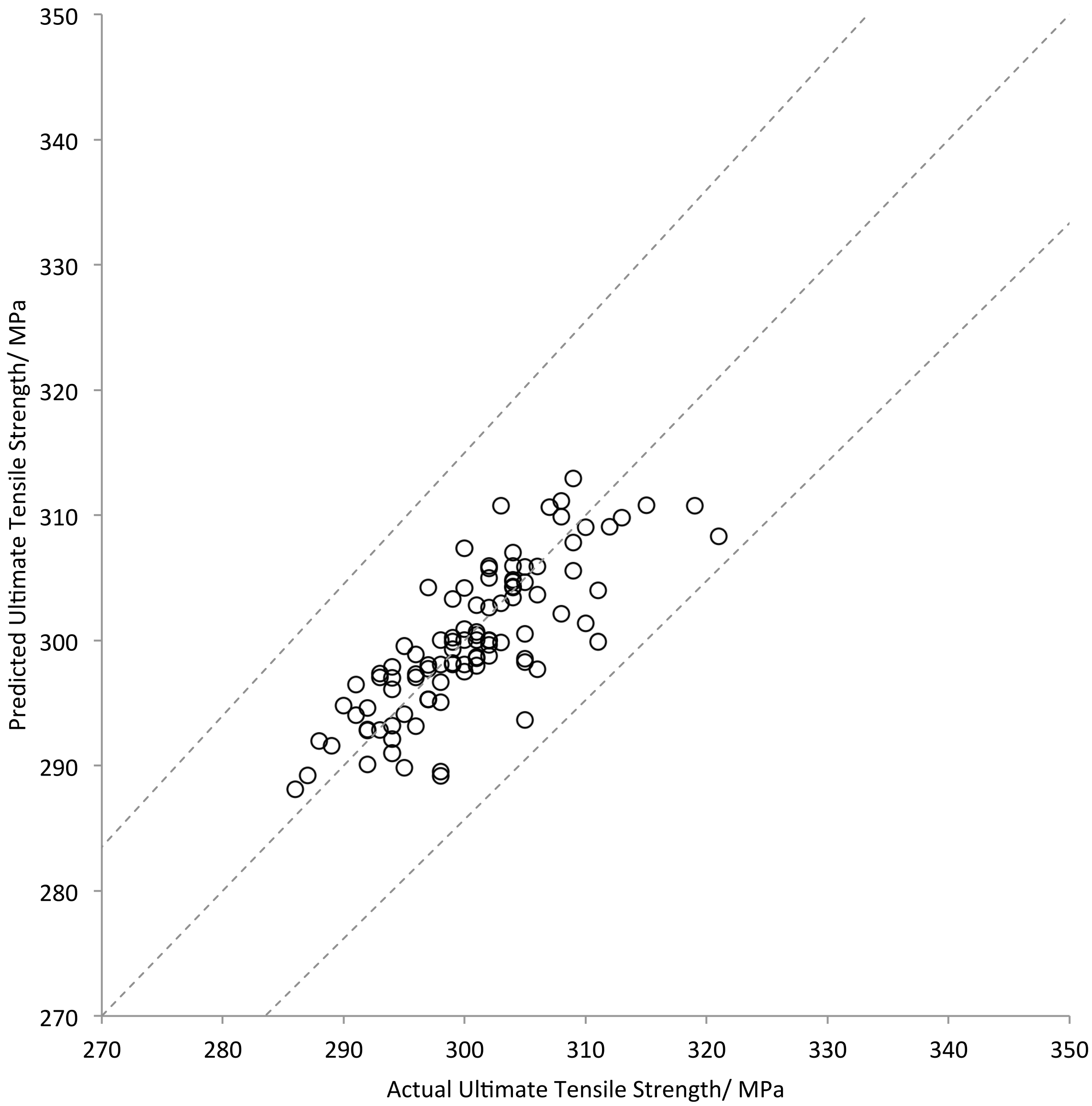


Figure 5.8: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and varying spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 0.7764. The following inputs were chosen:

Physical: gauge

Zodiac: snout temperature, pot temperature, roll 30 temperature, water quench temperature and temper mill tension out

Hot Rolling: drop temperature and finishing temperature

Chemistry: carbon, phosphorus, manganese, tin, nitrogen, aluminium (soluble) niobium, titanium, molybdenum, arsenic and titanium excess

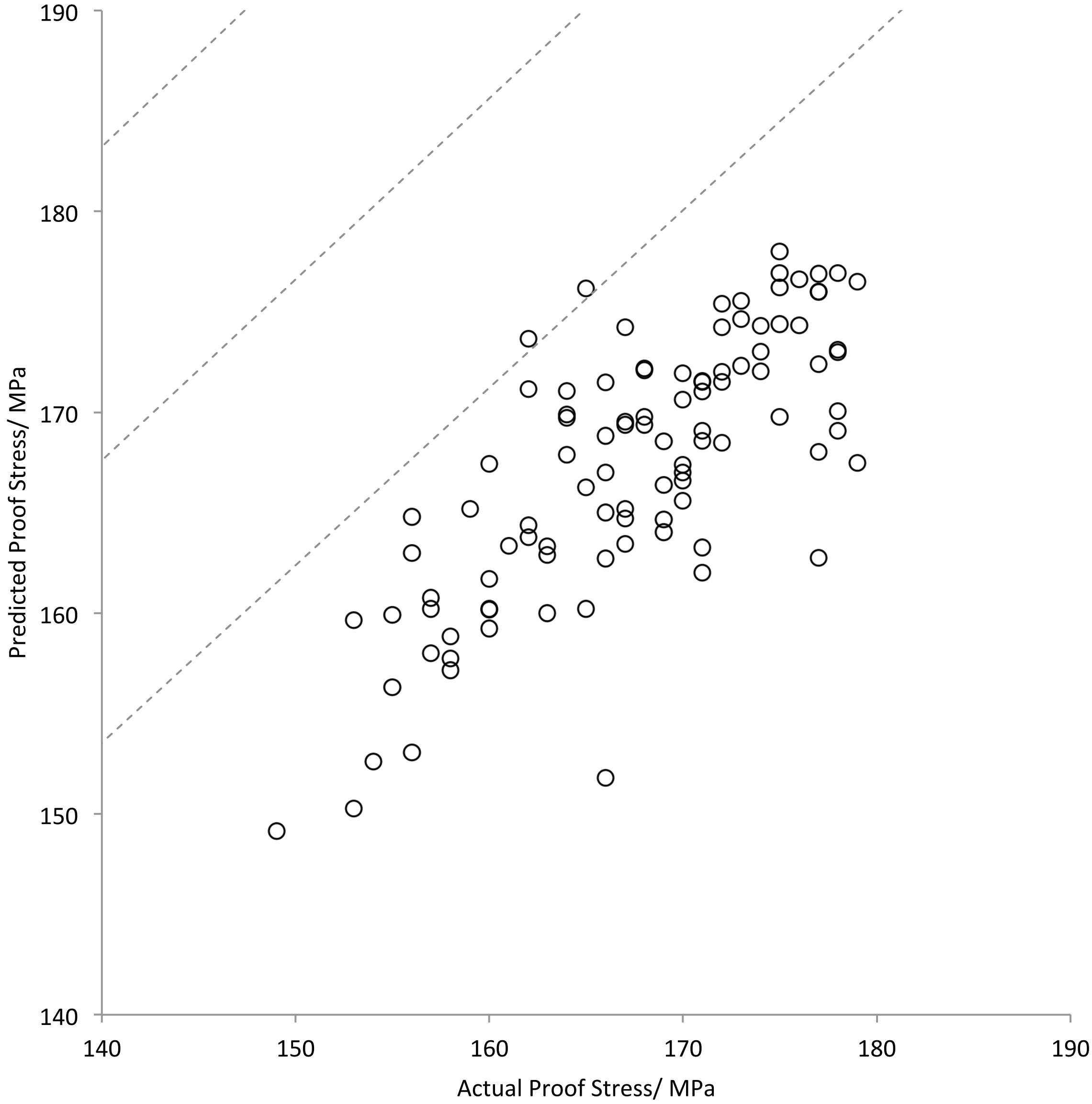


Figure 5.9: Actual proof stress values against proof stress values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and varying spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the proof stress model was found to be 0.6213. The following inputs were chosen:

Physical: gauge
Zodiac: snout temperature, roll 30 temperature, temper mill load and line speed
Hot Rolling:
Chemistry: carbon, silicon, phosphorus, nickel, copper, tin, nitrogen, aluminium (total), boron, titanium, molybdenum and chromium

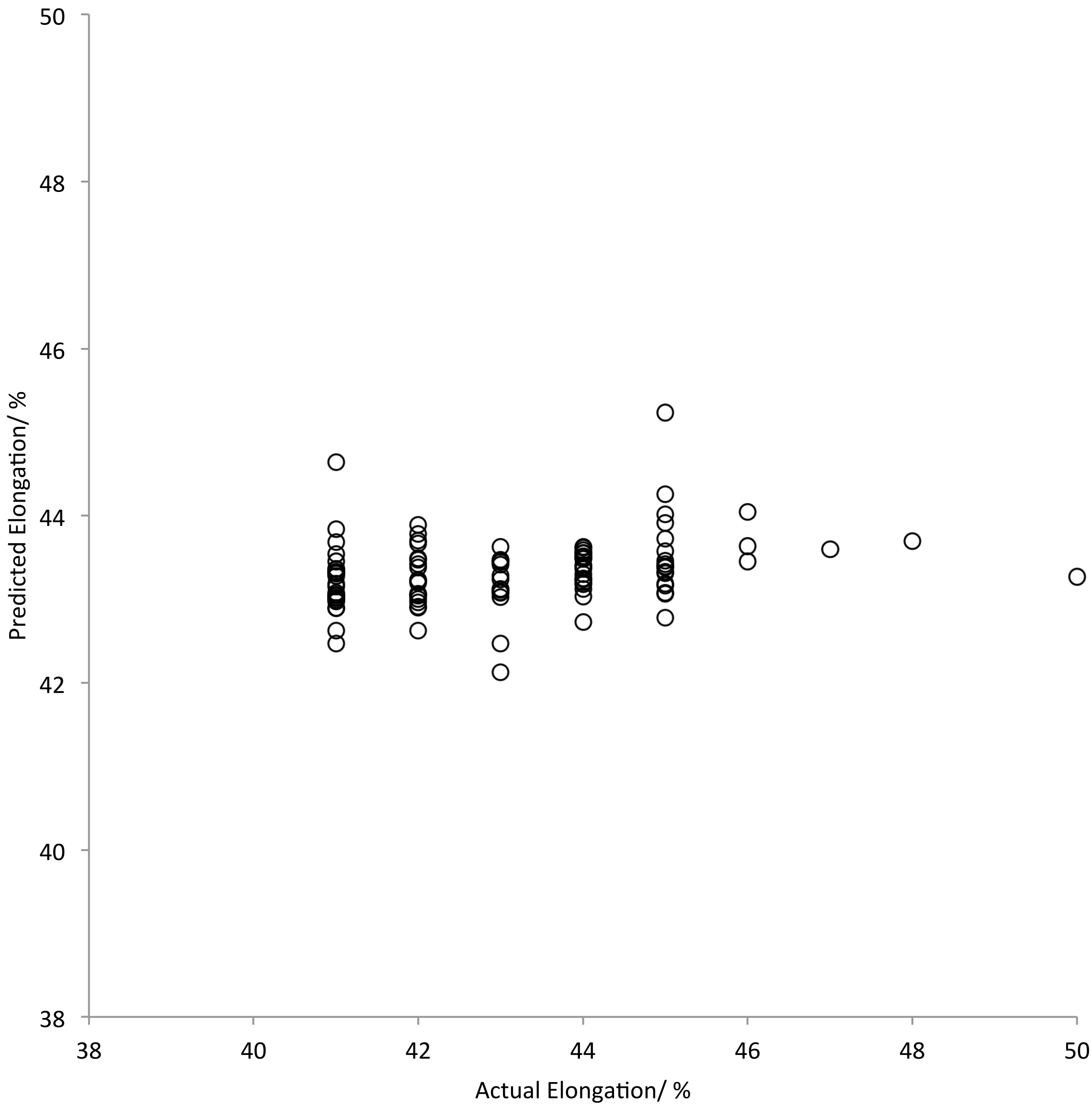


Figure 5.10: Actual elongation values against elongation values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and varying spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the elongation model was found to be 1.3571. The following inputs were chosen:

Physical: gauge, length and weight

Zodiac: direct fire temperature, snout temperature, water quench temperature, coating weight and line speed

Hot Rolling: finishing temperature

Chemistry: silicon, sulphur, tin, nitrogen, aluminium (total), molybdenum and titanium excess

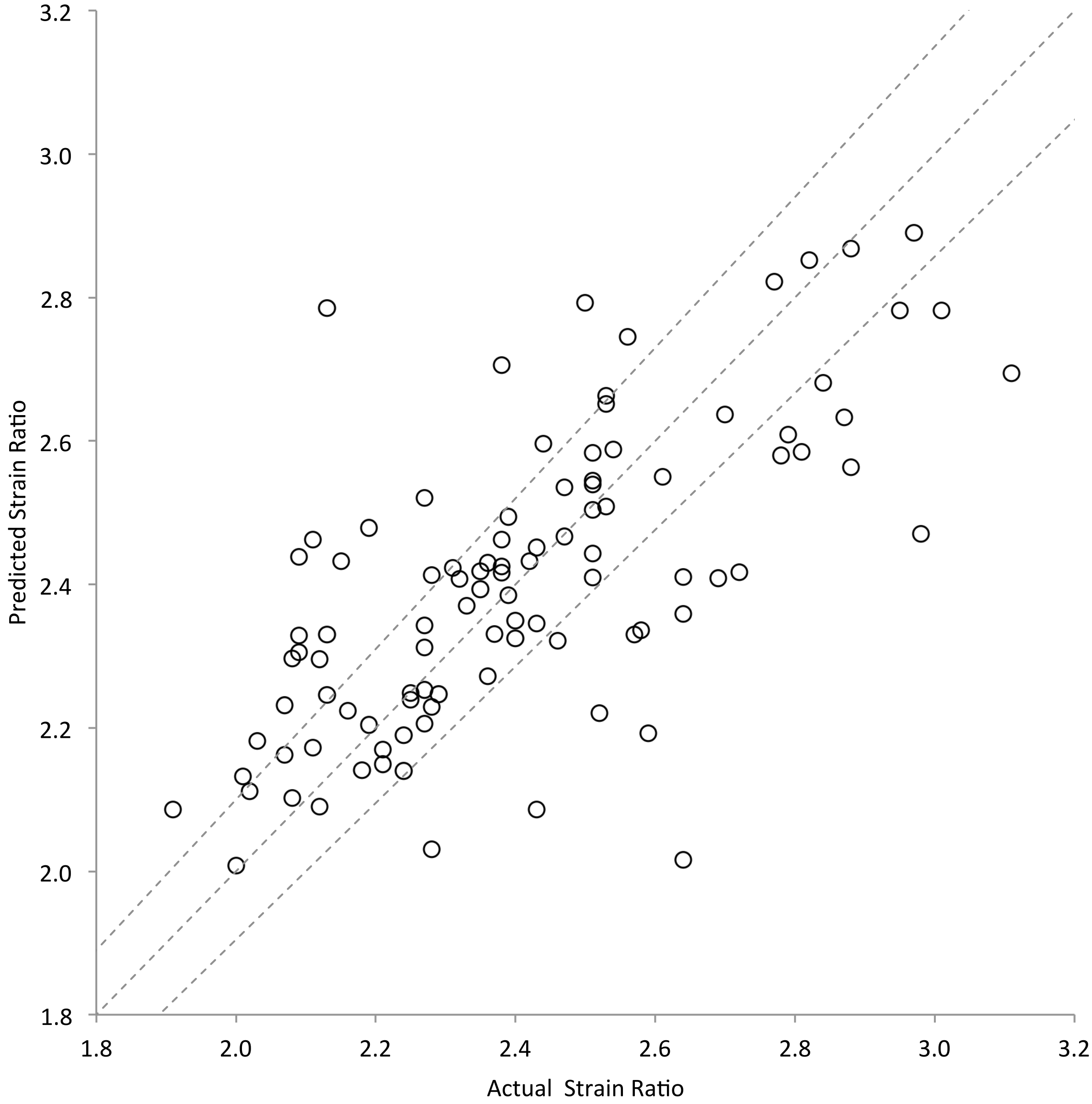


Figure 5.11: Actual strain ratio values against strain ratio values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and varying spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 0.9187. The following inputs were chosen:

Physical:	width and cold reduction
Zodiac:	direct fire temperature, snout temperature, coating weight and temper mill load
Hot Rolling:	drop temperature and rougher temperature
Chemistry:	carbon, phosphorus, nickel, copper, tin, nitrogen, aluminium (soluble), boron, titanium, molybdenum and chromium

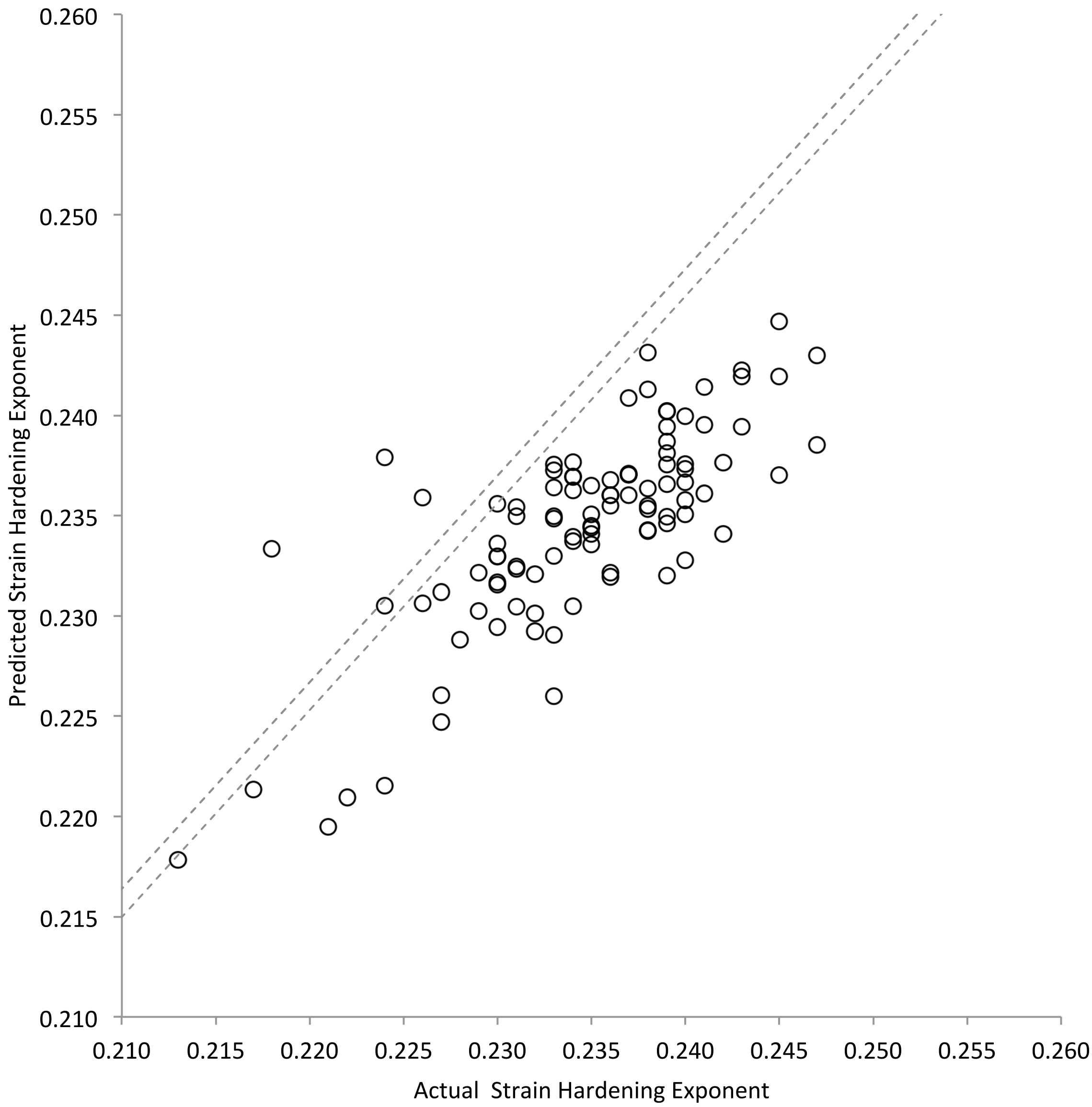


Figure 5.12: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for 3004/05 steels meeting specification trained using a genetic algorithm and varying spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain hardening exponent model was found to be 0.8268. The following inputs were chosen:

Physical:

Zodiac: radiant tube furnace start temperature, pot temperature, snout temperature, coating weight, temper mill load and line speed

Hot Rolling: drop temperature

Chemistry: carbon, phosphorus, manganese, nickel, copper, vanadium, aluminium (soluble), niobium, boron and titanium excess

Table 5.2: Statistical data produced from validation data set from a generalised regression model of 3004/05 steels meeting specification trained using a genetic algorithm and varying spread value

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	16.7	4.1	1.02%	0.80
Proof stress	22.2	4.7	2.07%	0.77
Elongation	3.00	1.73	3.29%	0.27
Strain ratio	0.038	0.19	5.93%	0.68
Strain hardening exponent	0.00002	0.004	1.26%	0.78

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Using this modified training routine failed to produce increases in the predictive accuracy of all the models produced by it. When there were increases in this value they were not significant enough, when compared to the previous approach, to warrant the extra training time the new approach required. The changes in root mean square error from the previous models were as follows: ultimate tensile strength 6.2%, proof stress 6.9%, elongation 1.6%, strain ratio -2.0% (increase) and strain hardening exponent 4.9%. The results from these models were in general better than those produced by the correlation based input model.

Training models using this approach required considerably more time than the previous approach, even though measures had been taken to try and minimise this increase. Models developed using this approach took between four and eight hours to train. The spread optimisation routine was called upon many more times in this model and was the main cause of this long training time, with each iteration requiring it to be run twenty five times. Most models took less than thirty iterations to complete the training routine. Only the ultimate tensile strength model terminated training due to the early stopping mechanisms employed. The proof stress and strain hardening exponent models took more steps to train; an interesting observation as these were the models whose predictive error had decreased.

One would assume that this modelling approach should be just as capable as the method used previously. Indeed, with the spread value optimised for every input set an improvement in the accuracy of these models would be expected. Models produced using this approach were found to show an improved accuracy when they required more iterations to complete. This suggests that changing the training routine to allow for more iterations would yield greater results. The simplest way of doing this would be to increase the number of loops that the training routine and early stopping mechanism required.

This approach was considered but there were limiting factors that prevented this line of investigation from being fully realised. The first of these was the time required to train the models. One may assume that doubling the number of loops would likely result in the training time also being doubled, meaning training times of nearly half a day for some of the models. Whilst these times may be acceptable for final models produced by a method similar to this that would be used on plant they are not practical for a research project. The second, and most limiting factor, was the amount of computing power that this increase would require. Training using the original configuration ran into the occasional problem, with Matlab exiting abruptly. The problem was always encountered during training runs that had taken a lot of iterations already, though the exact cause for this was unknown and due to the random nature of some of the training routine they were not repeatable.

5.3.3. Conclusions on the Different Approaches

Both methods of combining the spread optimisation routine with a genetic algorithm for input optimisation were able to produce models of a greater accuracy than the correlation input based models that had been developed previously for the majority of properties under investigation. This increase in accuracy came at the expense of training time, with times now measured in hours rather than minutes. Using a constant spread value for all iterations in a loop before optimising it to the best input set was found to provide the best compromise between training time and model accuracy. Optimising the spread value for each input set did not yield the expected increase in model accuracy.

Based on these results it was decided to continue this research using the constant spread option, as the benefits of using the other method were far outweighed by the time implications. For future work the early stopping mechanisms developed for the varying spread approach would also be employed as part of the constant spread training model. The impact due to an increase in the number of loops used by the varying spread approach should also be investigated, however due to time and computing restraints it would not be as part of this project.

The results suggest that the models predicting the ultimate tensile strength, proof stress and strain hardening exponent could be used to predict these properties with a good degree of accuracy for coils of the same grade. While the strain ratio predictions are not up to this standard the results from this model suggest that the model could be used to help analyse the steel making process, negating the need for as many test coils to be rolled. As with the previous models predicted values of the elongation values were poor when compared to the other properties. Further investigation into the cause of this problem and methods of rectifying is required.

5.4. Predictions from Additional Grades Using the Genetic Algorithm Approach

5.4.1. Previously Investigated Grades

With a suitable method of integrating a genetic algorithm into the model training routine found new model were developed to predict the properties of the other grades investigated during this project. The first of these focused on the DC05/06 steels that were used during the initial research. The results from these models are shown in Figures 5.13 to 5.17. Statistical data about these results is given in Table 5.3. As before, lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results.

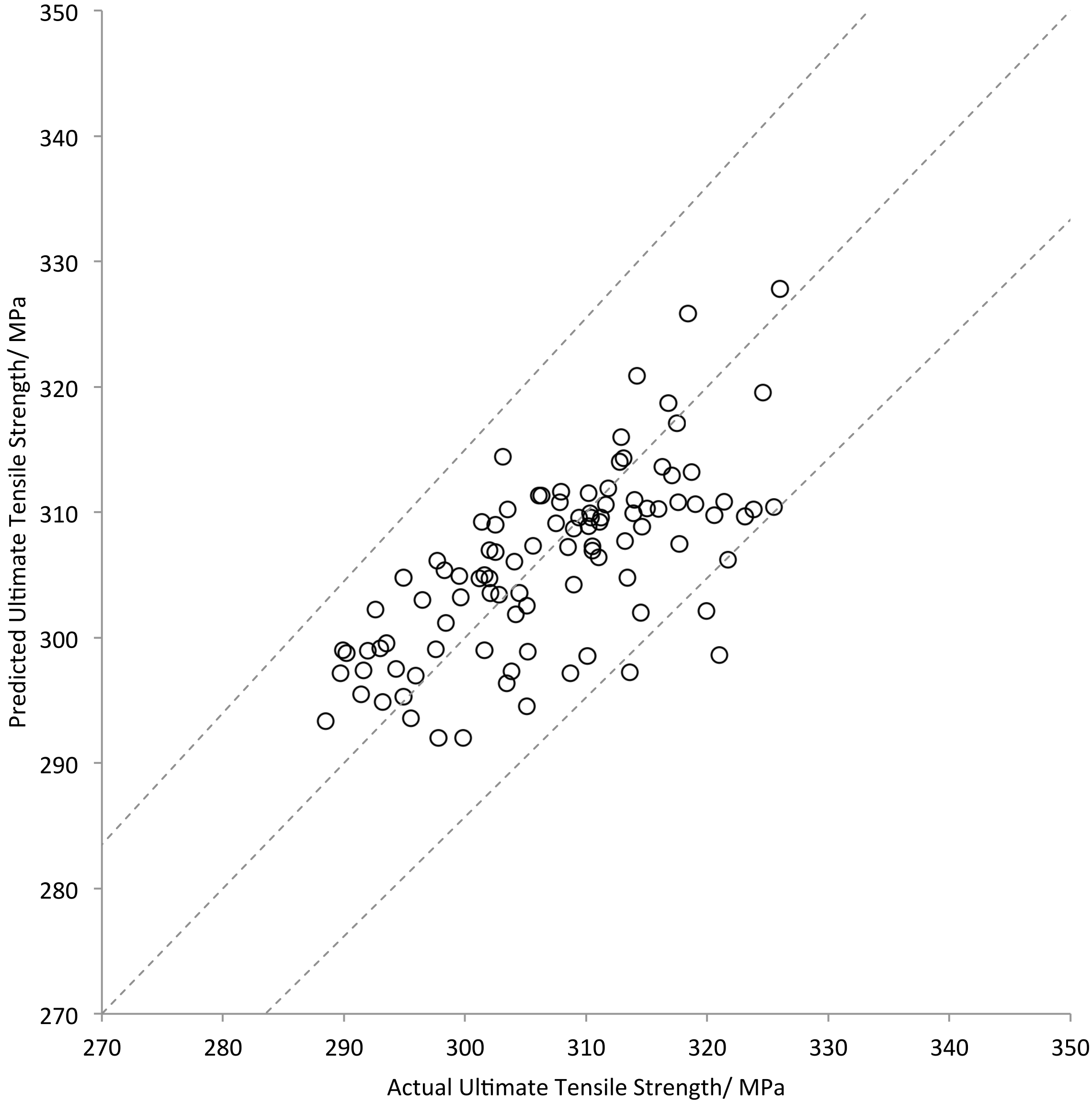


Figure 5.13: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for DC05/06 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 0.8800.

The following inputs were chosen:

Physical:	gauge, width and cold reduction
CAPL:	second cooling temperature, furnace tension, temper mill tension in and temper mill tension out
Hot Rolling:	rougher temperature
Chemistry:	carbon, sulphur, phosphorus, nickel, tin, vanadium, nitrogen, aluminium (total), aluminium (soluble) and boron

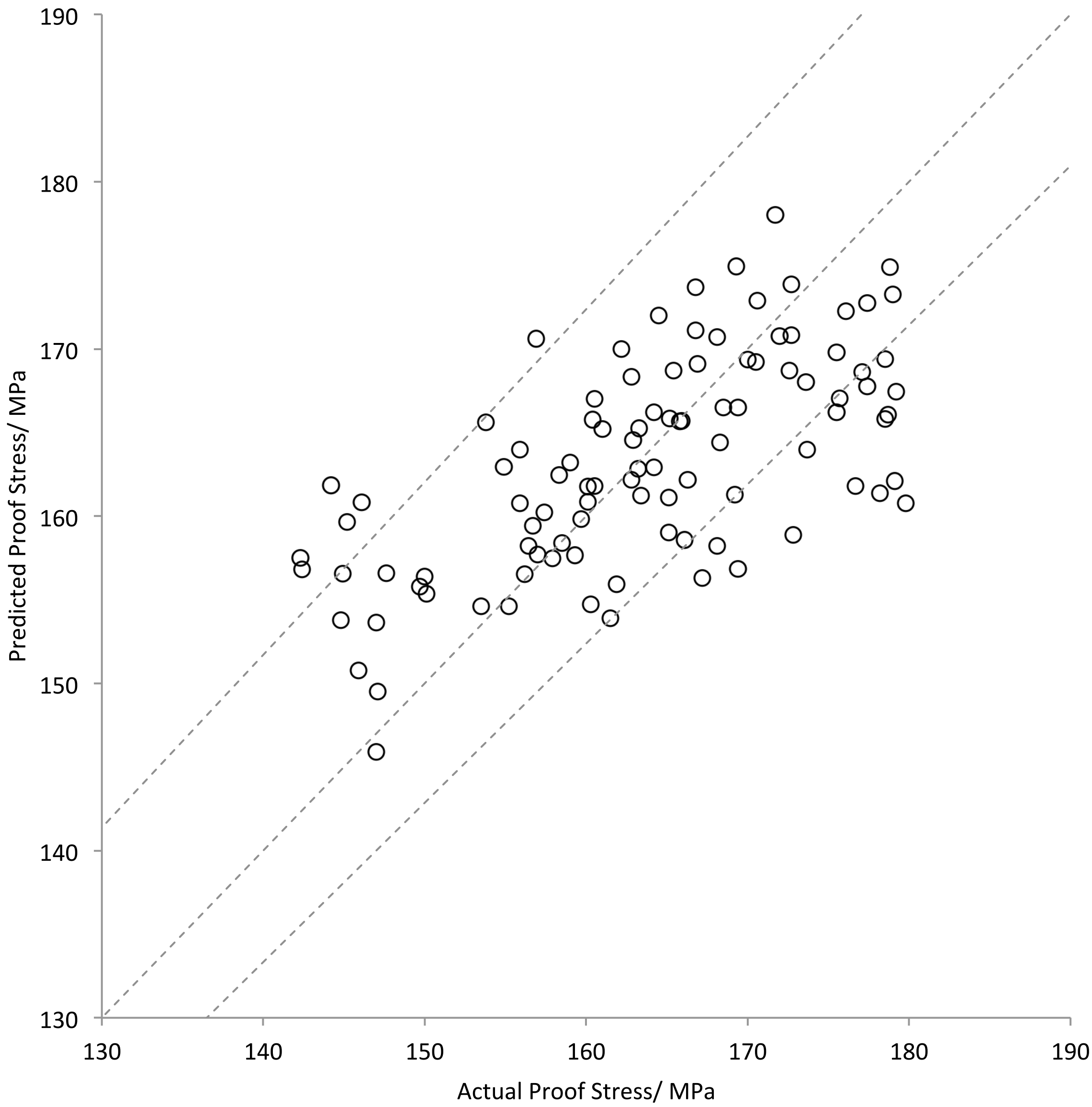


Figure 5.14: Actual proof stress values against proof stress values predicted by a generalised regression model for DC05/06 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the proof stress model was found to be 1.4499. The following inputs were chosen:

Physical:	width and cold reduction
CAPL:	radiant tube furnace temperature, soak temperature, controlled gas jet cooling temperature, reheat overage temperature, overage temperature, second cooling temperature, HGJC rate, temper mill tension out, temper mill speed and temper mill extension
Hot Rolling:	drop temperature, finishing temperature and coiling temperature
Chemistry:	silicon, sulphur, phosphorus, manganese, tin, vanadium, nitrogen, aluminium (total), aluminium (soluble), niobium, boron and chromium

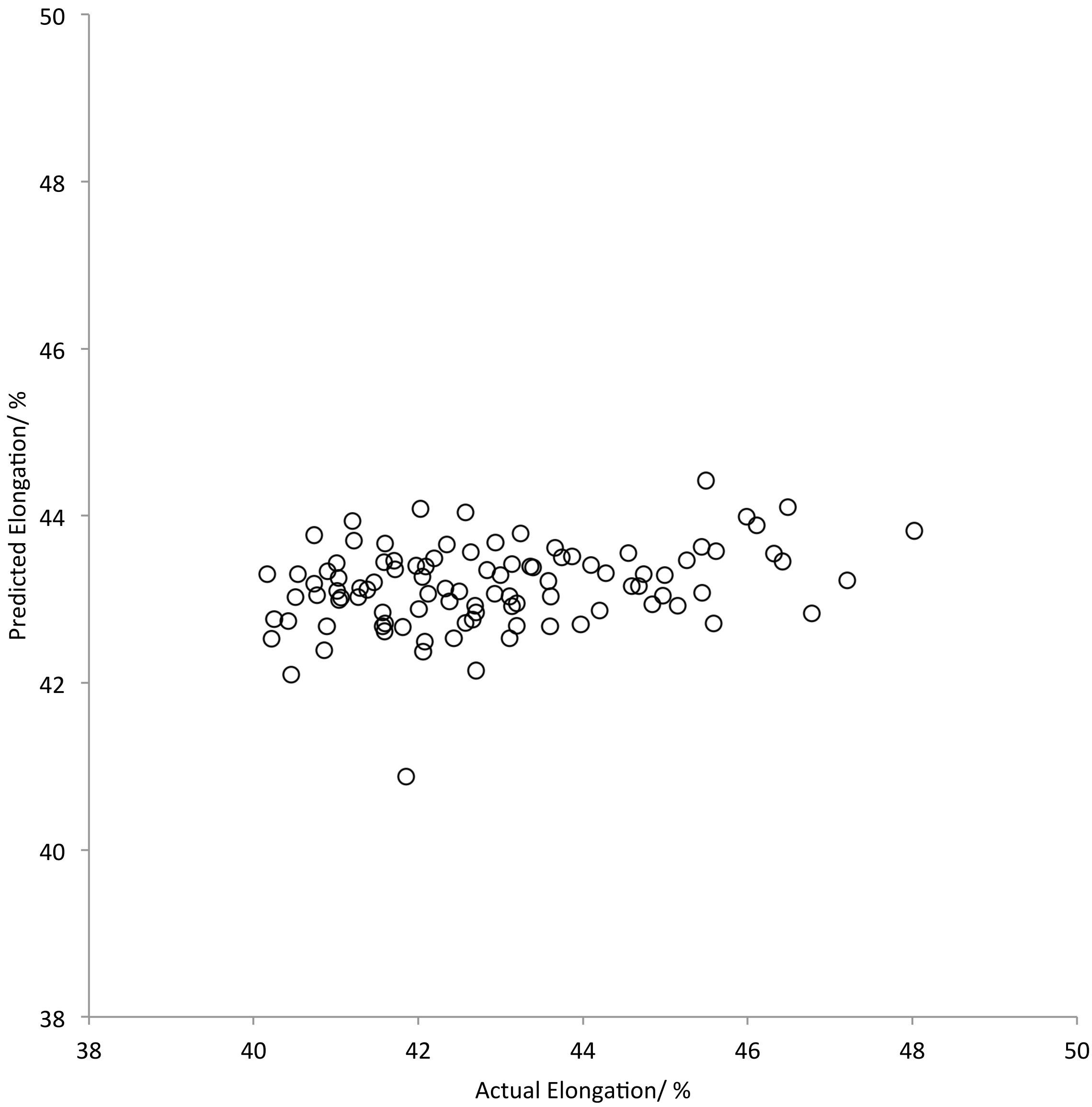


Figure 5.15: Actual elongation values against elongation values predicted by a generalised regression model for DC05/06 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the elongation model was found to be 1.0096. The following inputs were chosen:

Physical:
CAPL: overage temperature, temper mill tension in and temper mill load
Hot Rolling: rougher temperature, finishing temperature and coiling temperature
Chemistry: silicon, manganese, nitrogen, niobium and titanium

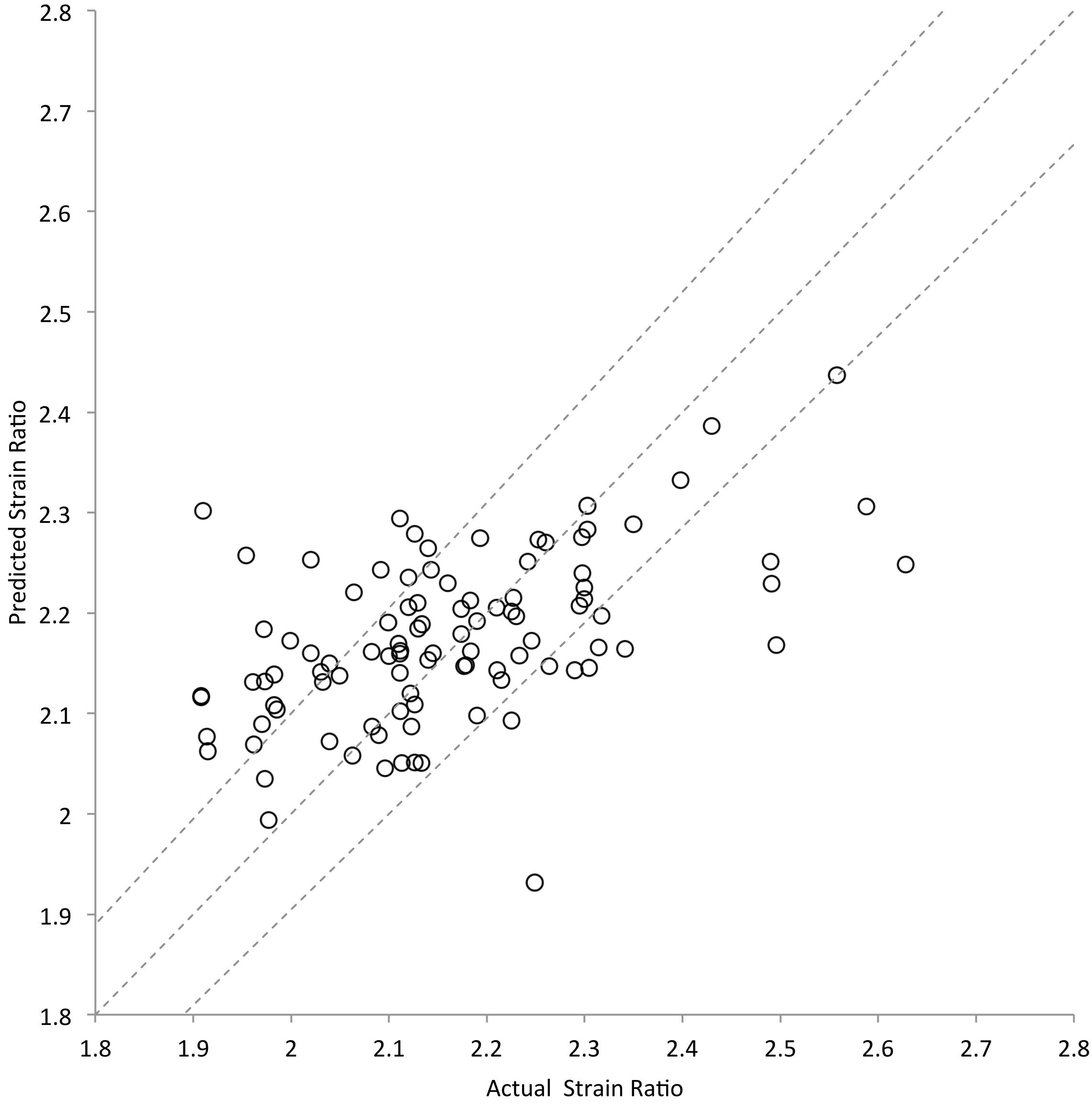


Figure 5.16: Actual strain ratio values against strain ratio values predicted by a generalised regression model for DC05/06 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 1.3692. The following inputs were chosen:

Physical:	gauge, width and cold reduction
CAPL:	soak temperature, controlled gas jet cooling temperature, reheat overage temperature, overage temperature, second cooling temperature, HGJC rate, soak time, temper mill tension out, and temper mill extension
Hot Rolling:	drop temperature
Chemistry:	carbon, phosphorus, manganese, nickel, vanadium, aluminium (total), boron, titanium and chromium

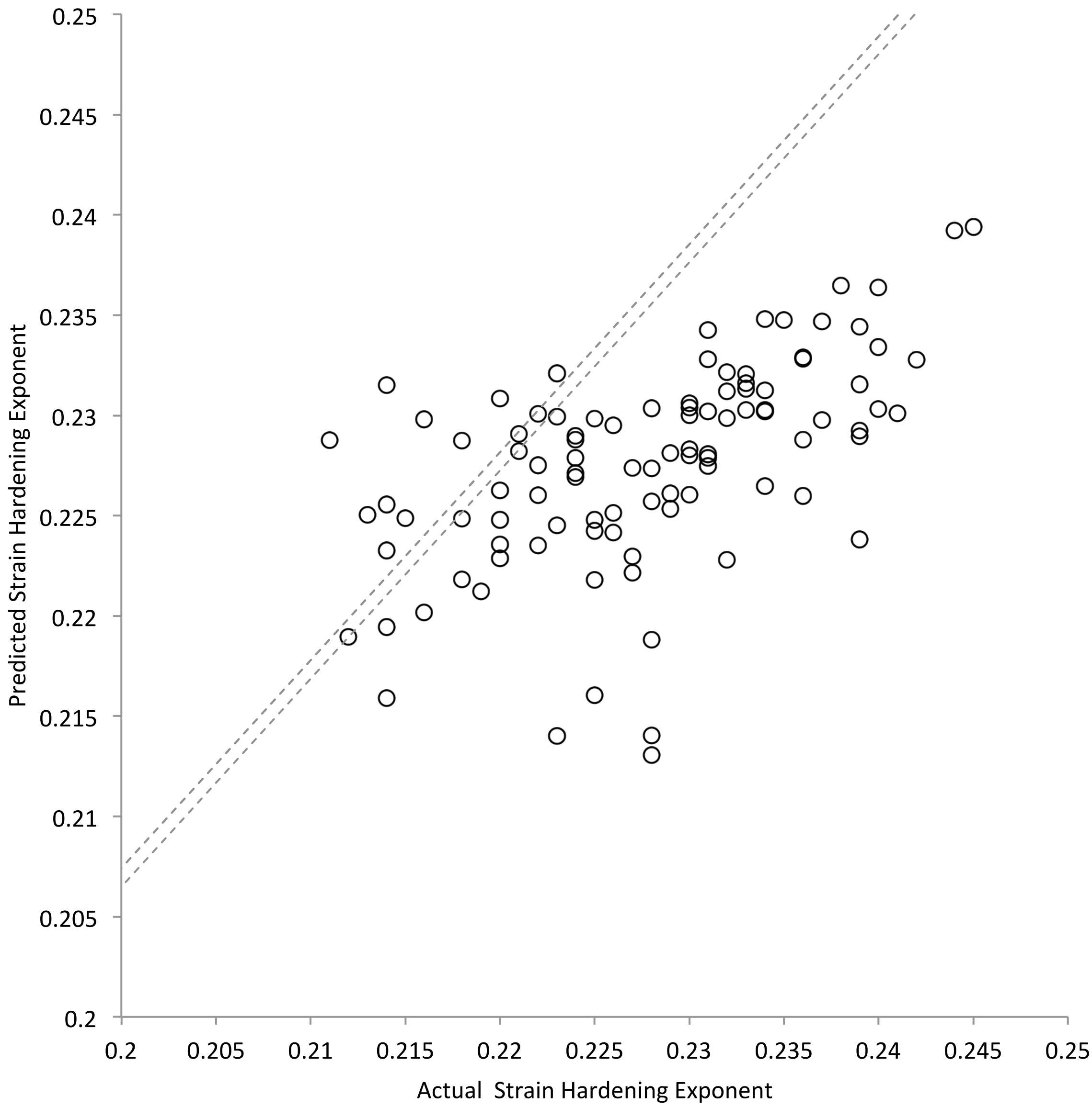


Figure 5.17: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for DC05/06 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 1.1706. The following inputs were chosen:

Physical: width and cold reduction
CAPL: reheat overage temperature, over temperature, second cooling temperature, furnace tension, temper mill tension out and temper mill extension
Hot Rolling: drop temperature, finishing temperature and coiling temperature
Chemistry: silicon, phosphorus, nickel, vanadium, nitrogen, aluminium (soluble) and chromium

Table 5.3: Statistical data produced from validation data set from a generalised regression model of DC05/06 steels meeting specification trained using a genetic algorithm and constant spread value

Property	**MSE**	**RMSE**	**MPE**	**R**
Ultimate tensile strength	49.2	7.0	1.79%	0.68
Proof stress	58.2	7.6	3.66%	0.65
Elongation	3.01	1.74	3.37%	0.30
Strain ratio	0.017	0.13	4.64%	0.51
Strain hardening exponent	0.00004	0.007	2.31%	0.56

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Using a generalised regression network with inputs selected using a genetic algorithm resulted in the predictive errors of all but one of the models predicting the properties of DC05/06 steels being lower than all other modelling approaches tried previously. The only model to see an increase in the predictive error was the strain hardening exponent model; the increase was very small. The reductions in the root mean square errors from the best previous models (generalised regression using all available inputs) were as follows: ultimate tensile strength 3.9%, proof stress 1.8%, elongation 0.8%, strain ratio 2.1% and strain hardening exponent -0.5% (increase).

Next models of the DC01/03/04 steels were produced. The results from these models are shown in Figures 5.18 to 5.22. Statistical data about these results is given in Table 5.4. As before, lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results.

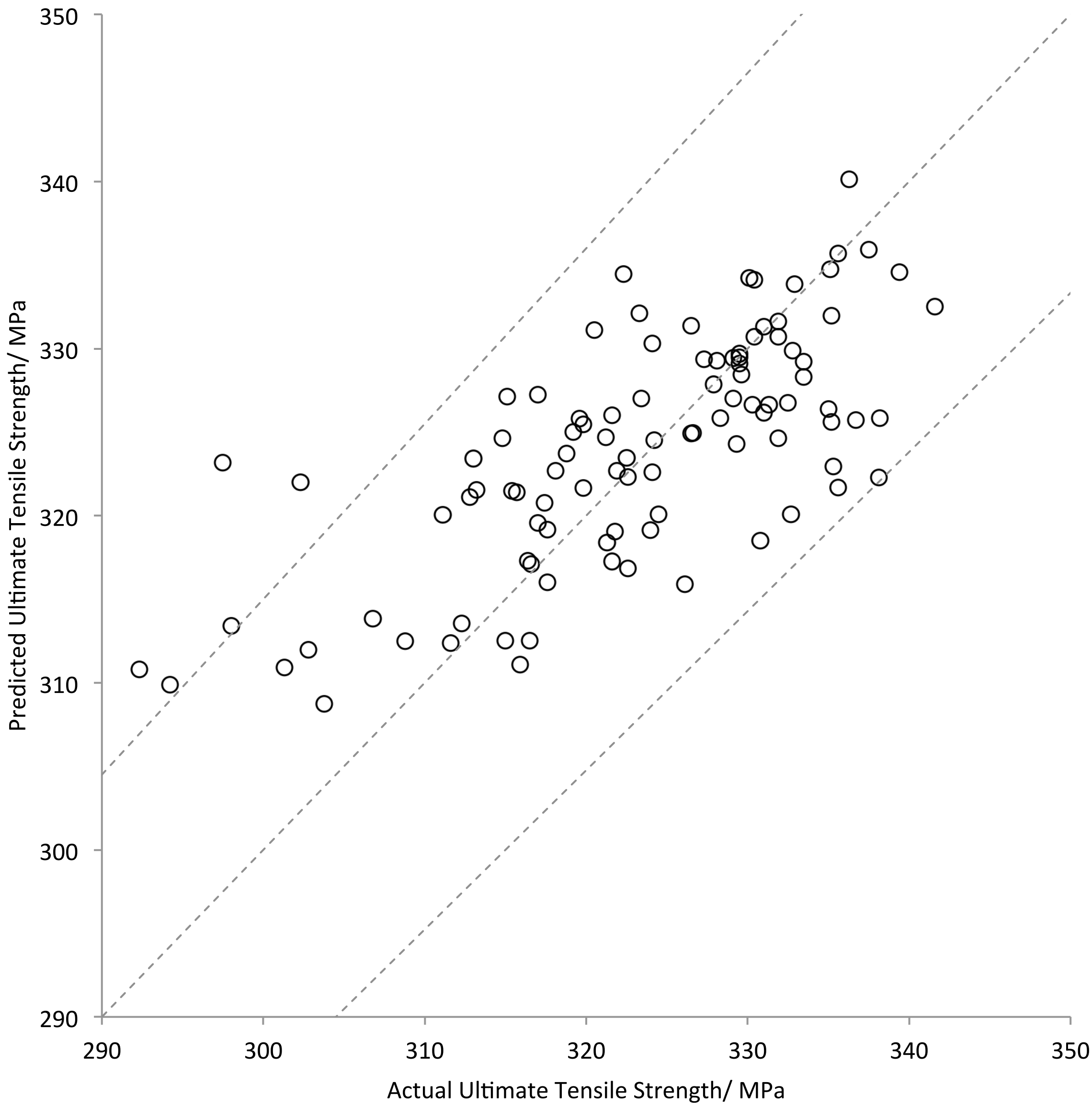


Figure 5.18: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for DC01/03/04 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 0.5821. The following inputs were chosen:

Physical: gauge, width and cold reduction

CAPL: radiant tube furnace temperature, soak temperature, controlled gas jet cooling temperature, high gas jet cooling temperature, reheat overage temperature, overage temperature, second cooling temperature, temper mill tension in, temper mill load, temper mill speed and temper mill extension

Hot Rolling: drop temperature

Chemistry: manganese, nickel, boron, chromium and titanium excess

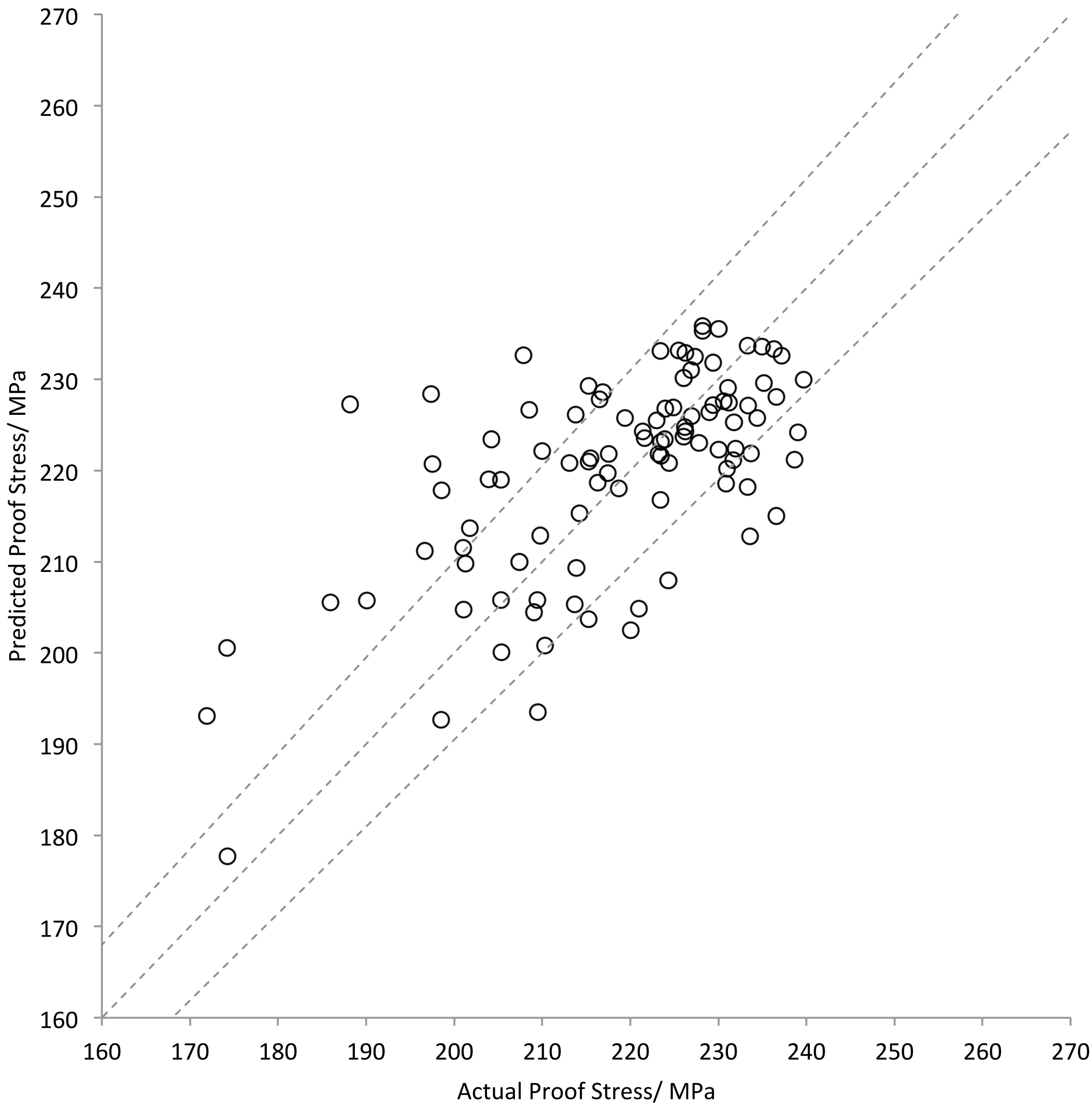


Figure 5.19: Actual proof stress values against proof stress values predicted by a generalised regression model for DC01/03/04 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the proof stress model was found to be 0.4162. The following inputs were chosen:

Physical:	width and weight
CAPL:	soak temperature, controlled gas jet cooling temperature, high gas jet cooling temperature, reheat overage temperature, overage temperature, HGJC rate, soak time, temper mil tension out and temper mill speed
Hot Rolling:	
Chemistry:	carbon, silicon, phosphorus, vanadium, nitrogen, niobium, boron, titanium, chromium and titanium excess

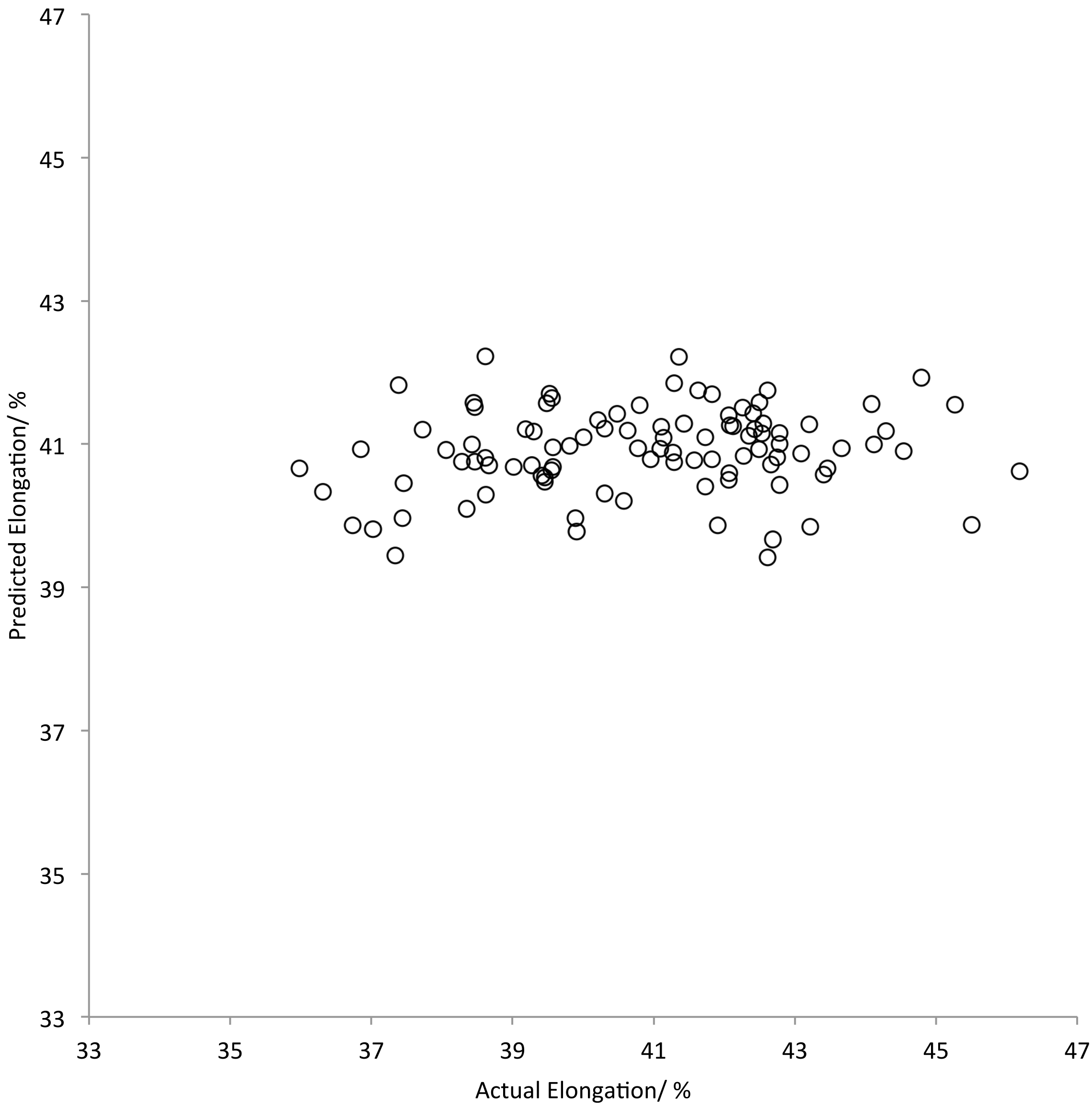


Figure 5.20: Actual elongation values against elongation values predicted by a generalised regression model for DC01/03/04 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the elongation model was found to be 0.4104. The following inputs were chosen:

Physical: cold reduction
CAPL: radiant tube furnace temperature, soak temperature, controlled gas jet cooling temperature, high gas jet cooling temperature and soak time
Hot Rolling:
Chemistry: carbon manganese and titanium excess

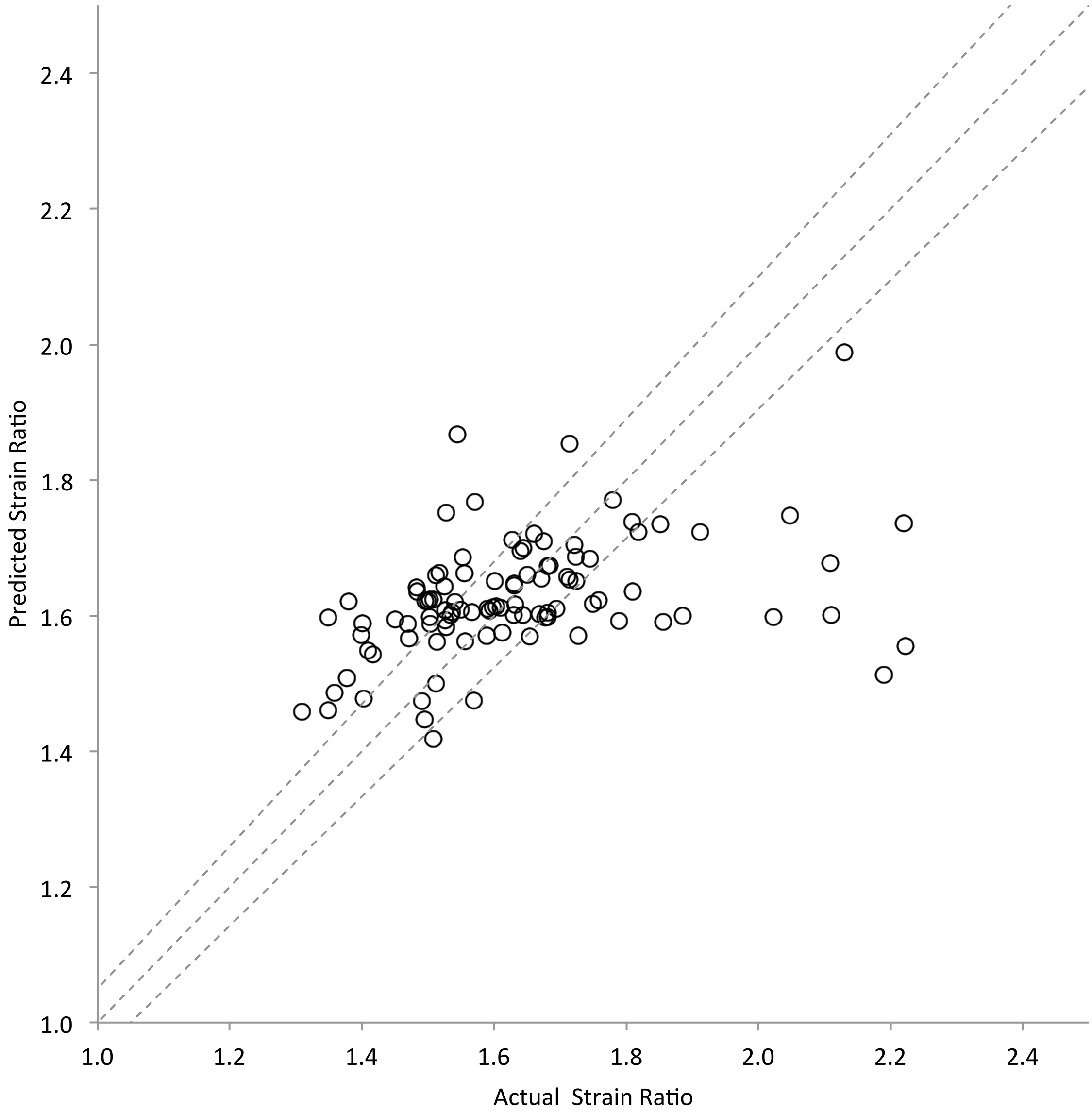


Figure 5.21: Actual strain ratio values against strain ratio values predicted by a generalised regression model for DC01/03/04 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 1.1334. The following inputs were chosen:

Physical: width

CAPL: radiant tube furnace temperature, soak temperature, high gas jet cooling temperature, overage temperature, second cooling temperature, HGJC rate, soak time, furnace tension, temper mill tension in, temper mill tension out, temper mill load and temper mill speed

Hot Rolling: drop temperature and coiling temperature

Chemistry: carbon, sulphur, phosphorus, manganese, tin, vanadium, nitrogen, aluminium (total), aluminium (soluble), niobium, boron, titanium, chromium and titanium excess

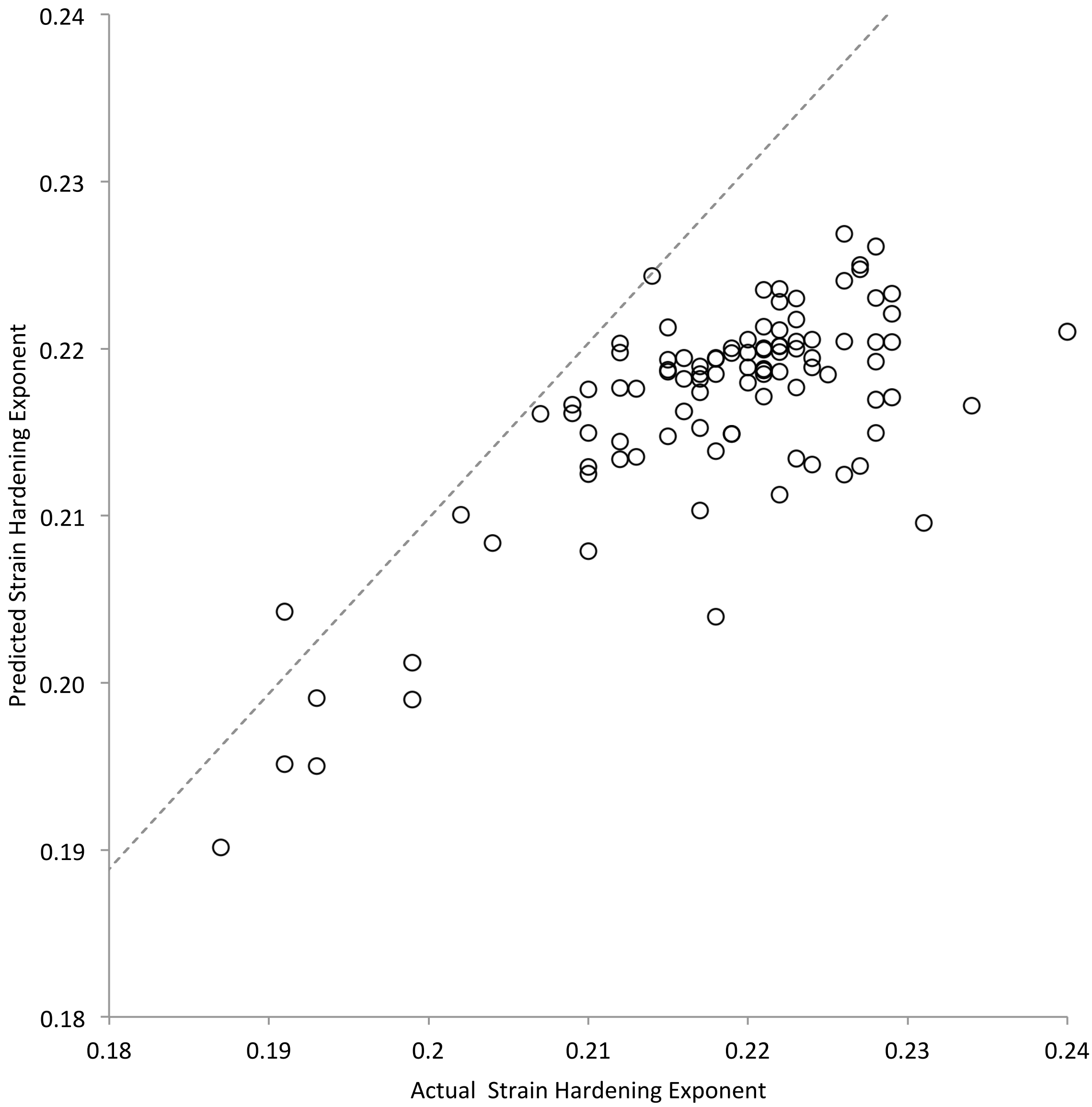


Figure 5.22: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for DC01/03/04 steels meeting specification trained using a genetic algorithm and constant spread value(Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 1.1438. The following inputs were chosen:

Physical:	gauge, weight and cold reduction
CAPL:	soak temperature, high gas jet cooling temperature, overage temperature, HGJC rate, furnace tension, temper mill tension out and temper mill speed
Hot Rolling:	rougher temperature and coiling temperature
Chemistry:	silicon, phosphorus, nickel, tin, nitrogen, aluminium (soluble), boron and chromium

Table 5.4: Statistical data produced from validation data set from a generalised regression model of DC01/03/04 steels meeting specification trained using a genetic algorithm and constant spread value

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	55.2	7.4	1.74%	0.72
Proof stress	132.1	11.5	4.16%	0.64
Elongation	5.50	2.35	4.63%	0.15
Strain ratio	0.031	0.18	7.21%	0.41
Strain hardening exponent	0.00004	0.006	2.16%	0.74

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

The results suggest that the models predicting the ultimate tensile strength, proof stress and strain hardening exponent could be used to predict these properties with a good degree of accuracy for coils of the same grade. Elongation and strain ratio prediction were found to be poor for this grade of steel. Further development of these models would be required for them to have any additional use. The reductions in the root mean square errors from the best previous models (generalised regression using correlation derived inputs) were as follows: ultimate tensile strength 6.7%, proof stress 2.0%, elongation 0.0% strain ratio 7.5% and strain hardening exponent 9.28%. Models of this grade of steel developed using the genetic algorithm approach took a considerable amount of time to train, all taking at least 24 hours to complete. The increase in training time was due to the considerably larger data sets used to produce these models.

5.4.2. Additional Zodiac Grades

Late into the development of this project data sets containing the processing information and mechanical properties for two additional grades of steel produced on Zodiac became available. The first of these, DX51, is a similar grade to the DC01/03/04 steels produced on CAPL. This data sets covered steels processed during the period January 2010 to July 2010. The second set, containing SD350/450 coils, represented a different family of steel grades to any of those studied previously, so would be a good test of the adaptability of the modelling process. This set covered steels produced during the period January 2010 to April 2011.

Slight differences between the current data sets and those used to produce the original Zodiac models meant that the current data was not compatible with the importing tool. Due to time restraints it was decided to sort the new data by hand so that it would be compatible, rather than to rewrite the importing tool. This allowed the investigation to be carried out within the remaining time frame of the project. Due to this the data importing and cleaning mechanisms that had been written previously could not be used in their entirety. Coils could not be checked against the required specifications, meaning that all available coils were selected regardless of their final properties. After data cleaning, the DX51 data set contained 1613 complete coils. The SD350/450 data set contained only 157 complete coils. Closer inspection of this data set revealed that some mechanical properties were not available for every coil. In order to try and model these steels, they would be selected based on individual mechanical properties and not the complete set.

To investigate the SD350/450 steels, data needed to be selected one property at a time, rather than inputting the whole data set into Matlab simultaneously. In the case of the ultimate tensile strength value, this meant that only 763 coils were selected. Past work has shown that poor results are achieved using a small amount of coil information. However, it was decided to try and model these steels anyway as this was the only data available at the time. For the proof stress 763 coils were again selected. Initial checks suggested that these were the same 763 coils selected for the ultimate tensile strength model. The maximum, minimum, mean, standard deviation and units of the inputs values and output properties from the cleaned data sets of DX51 and SD350/450 are shown in Tables 5.5 and 5.6 respectively. A slight change in the processing of these coils meant that the temper mill elongation value was selected as a possible input rather that the temper mill load.

The results from the DX51 models are shown in Figures 5.23 to 5.27. Statistical data about these results is given in Table 5.7. As before, lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results.

Table 5.5: DX51 cleaned data set input conditions and output properties

Quantity	Max	Min	Means	Std	Unit
Gauge	2.01	0.44	1.13	0.44	mm
Width	1527	950	1285	132	mm
Weight	28.10	4.58	16.54	5.36	tonnes
Direct Fire (DF) (average)	746.15	460.00	606.72	28.76	^oC
Radiant Tube Furnace Start (RTFS) (average)	840.21	557.42	707.94	27.05	^oC
Snout (average)	902.69	400.53	471.20	15.95	^oC
Water Quench (WQ) (average)	488.10	50.07	94.69	20.93	^oC
Coating Weight	177	49	119	30	g/m^2
Length	6057	305	1711	965	m
Line Speed	151.20	30.00	111.89	29.53	m/min
Temper Mill Extension (TME)	1.47	0.04	0.16	0.27	%
Temper Mill Tension In (TMTI)	1210.13	2029.26	5751.10	1445.52	KN
Hot Rolled Drop Temperature	1294	1155	1213	19	^oC
Hot Rolled Coiling Temperature	615	570	601	3	^oC
Hot Rolled Finishing Temperature	925	850	894	8	^oC
Hot Rolled Stand 5 Temperature (HRS5)	1144	1022	1096	17	^oC
Cold Reduction	0.810	0.534	0.659	0.067	%
Hot Dip Pot Temperature (average)	668.07	452.77	463.50	7.50	^oC
Roll 30 Temperature (average)	200.81	50.00	137.67	22.02	^oC
Radiant Tube Furnace End (RTFE) (average)	853.04	643.59	727.28	24.98	^oC
Temper Mill Tension Out (TMTO)	9178.00	2073.16	6048.82	1545.69	kN
Molybdenum (Mo)	0.0050	0.0010	0.0011	0.0003	%wt
Calcium (Ca)	0.0000	0.0000	0.0000	0.0000	%wt
Carbon (C)	0.1030	0.0190	0.0455	0.0095	%wt
Silicon (Si)	0.0240	0.0010	0.0036	0.0030	%wt
Sulphur (S)	0.0300	0.0042	0.0199	0.0055	%wt
Phosphorus (P)	0.0270	0.0040	0.0122	0.0043	%wt
Manganese (Mn)	0.4460	0.1140	0.2036	0.0484	%wt
Nickel (Ni)	0.0260	0.0070	0.0124	0.0027	%wt
Copper (Cu)	0.0400	0.0070	0.0179	0.0063	%wt
Tin (Sn)	0.0240	0.0010	0.0037	0.0021	%wt
Vanadium (V)	0.0020	0.0010	0.0010	0.0000	%wt
Nitrogen (N)	0.0089	0.0018	0.0035	0.0010	%wt
Aluminium (Al) (Total)	0.0930	0.0180	0.0384	0.0089	%wt
Aluminium (Al) (Soluble)	0.0860	0.0170	0.0357	0.0083	%wt
Niobium (Nb)	0.0020	0.0010	0.0010	0.0001	%wt
Boron (B)	0.0033	0.0001	0.0001	0.0003	%wt
Titanium (Ti)	0.0040	0.0010	0.0013	0.0005	%wt
Chromium (Cr)	0.0520	0.0060	0.0159	0.0046	%wt
Titanium Excess (Ti*)	-0.1172	-0.4520	-0.2224	0.0383	
Ultimate Tensile Stregth (Rm)	430	329	366	14	N/mm^2
Proof Stress (Re)	374	207	299	22	N/mm^2
Elongation (A)	45	20	36	3	%
Strain Ratio (r)	2.45	1.01	1.58	0.19	
Strain Hardening Exponent (n)	0.280	0.133	0.204	0.026	

Table5.6: SD350/450 cleaned data set input conditions and output properties

Quantity	**Max**	**Min**	**Means**	**Std**	**Unit**
Gauge	1.99	0.78	1.21	0.27	mm
Width	1425	953	1154	120	mm
Weight	25.15	5.94	14.95	5.06	tonnes
Direct Fire (DF) (average)	729.66	564.50	619.09	29.54	^oC
Radiant Tube Furnace Start (RTFS) (average)	849.32	413.05	726.17	25.75	^oC
Snout (average)	498.82	446.12	471.00	8.98	^oC
Water Quench (WQ) (average)	310.23	50.07	98.21	16.08	^oC
Coating Weight	180	50	137	12	g/m^2
Length	2715	477	1401	508	m
Line Speed	150.00	42.00	104.70	21.42	m/min
Temper Mill Extension (TME)	2.04	0.06	1.48	0.17	%
Temper Mill Tension In (TMTI)	9425.17	2522.00	6163.51	1487.97	KN
Hot Rolled Drop Temperature	1274	1151	1230	16	^oC
Hot Rolled Coiling Temperature	676	569	620	18	^oC
Hot Rolled Finishing Temperature	915	855	893	6	^oC
Hot Rolled Stand 5 Temperature (HRS5)	1148	1046	1103	16	^oC
Cold Reduction	0.757	0.287	0.564	0.040	%
Hot Dip Pot Temperature (average)	550.17	453.55	462.00	4.32	^oC
Roll 30 Temperature (average)	181.59	50.00	141.89	19.82	^oC
Radiant Tube Furnace End (RTFE) (average)	846.34	669.36	738.51	25.37	^oC
Temper Mill Tension Out (TMTO)	8701.65	2730.00	5656.52	1161.81	kN
Molybdenum (Mo)	0.0040	0.0010	0.0011	0.0004	%wt
Calcium (Ca)	0.0007	0.0001	0.0002	0.0001	%wt
Carbon (C)	0.0790	0.0015	0.0620	0.0057	%wt
Silicon (Si)	0.0250	0.0020	0.0079	0.0043	%wt
Sulphur (S)	0.0220	0.0050	0.0147	0.0029	%wt
Phosphorus (P)	0.0870	0.0150	0.0721	0.0062	%wt
Manganese (Mn)	1.2130	0.0990	0.3598	0.1782	%wt
Nickel (Ni)	0.0310	0.0080	0.0148	0.0038	%wt
Copper (Cu)	0.0420	0.0100	0.0222	0.0082	%wt
Tin (Sn)	0.0170	0.0010	0.0040	0.0024	%wt
Vanadium (V)	0.0030	0.0010	0.0011	0.0003	%wt
Nitrogen (N)	0.0080	0.0022	0.0045	0.0010	%wt
Aluminium (Al) (Total)	0.0780	0.0210	0.0407	0.0063	%wt
Aluminium (Al) (Soluble)	0.0720	0.0200	0.0377	0.0059	%wt
Niobium (Nb)	0.0380	0.0010	0.0203	0.0040	%wt
Boron (B)	0.0007	0.0001	0.0001	0.0001	%wt
Titanium (Ti)	0.0480	0.0010	0.0027	0.0018	%wt
Chromium (Cr)	0.0300	0.0100	0.0174	0.0041	%wt
Titanium Excess (Ti*)	0.0226	-0.3602	-0.2827	0.0245	
Ultimate Tensile Stregth (Rm)	756	338	491	36	N/mm^2
Proof Stress (Re)	726	163	389	37	N/mm^2

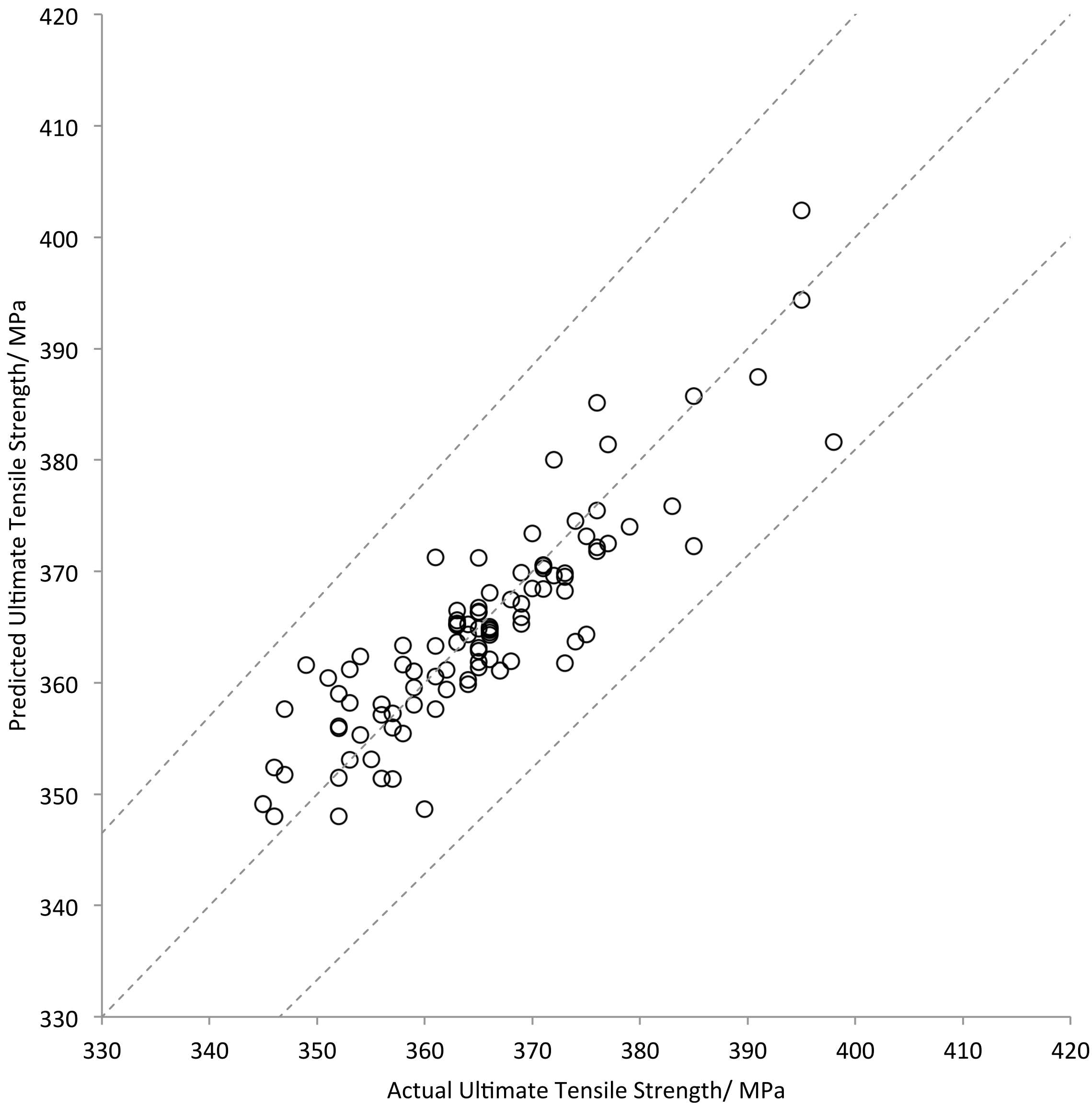


Figure 5.23: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for DX51 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 1.4260. The following inputs were chosen:

Physical:	gauge, length and cold reduction
Zodiac:	direct fire temperature, radiant tube furnace exit temperature, roll 30 temperature, coating weight, temper mill tension in, temper mil tension out, temper mill extension and line speed
Hot Rolling:	rougher temperature, finishing temperature and coiling temperature
Chemistry:	carbon, silicon, sulphur, phosphorus, manganese, copper, vanadium, nitrogen, aluminium (total), boron, titanium, chromium and titanium excess

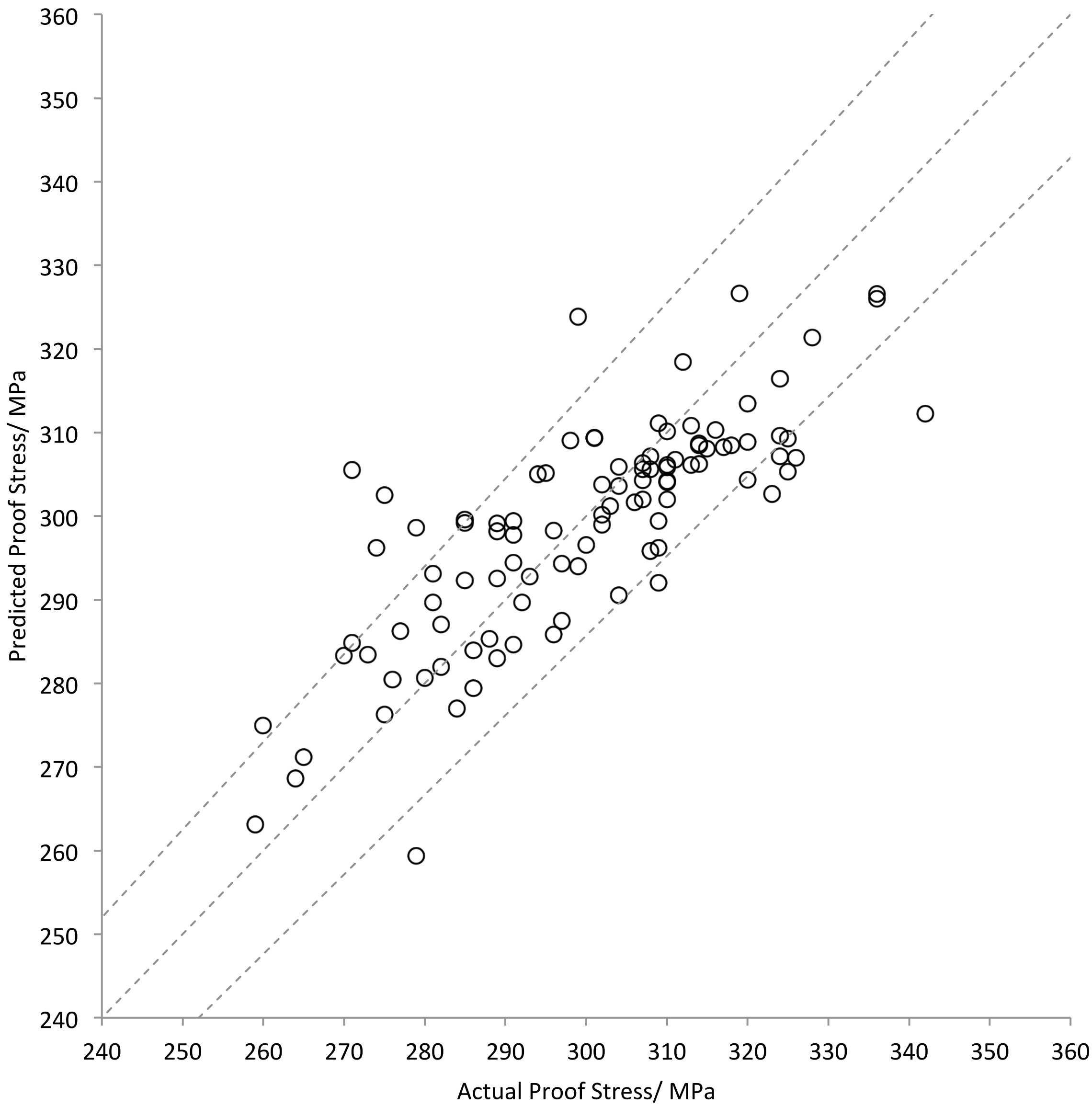


Figure 5.24: Actual proof stress values against proof stress values predicted by a generalised regression model for DX51 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the proof stress model was found to be 1.6985. The following inputs were chosen:

Physical:	gauge, weight and cold reduction
Zodiac:	radiant tube furnace start temperature, pot temperature, water quench temperature, coating weight, temper mill tension in, temper mill tension out, temper mil extension and line speed
Hot Rolling:	rougher temperature and finishing temperature
Chemistry:	carbon, silicon, sulphur, phosphorus, manganese, nickel, copper, tin, vanadium, aluminium (total), aluminium (soluble), niobium, boron, molybdenum and chromium

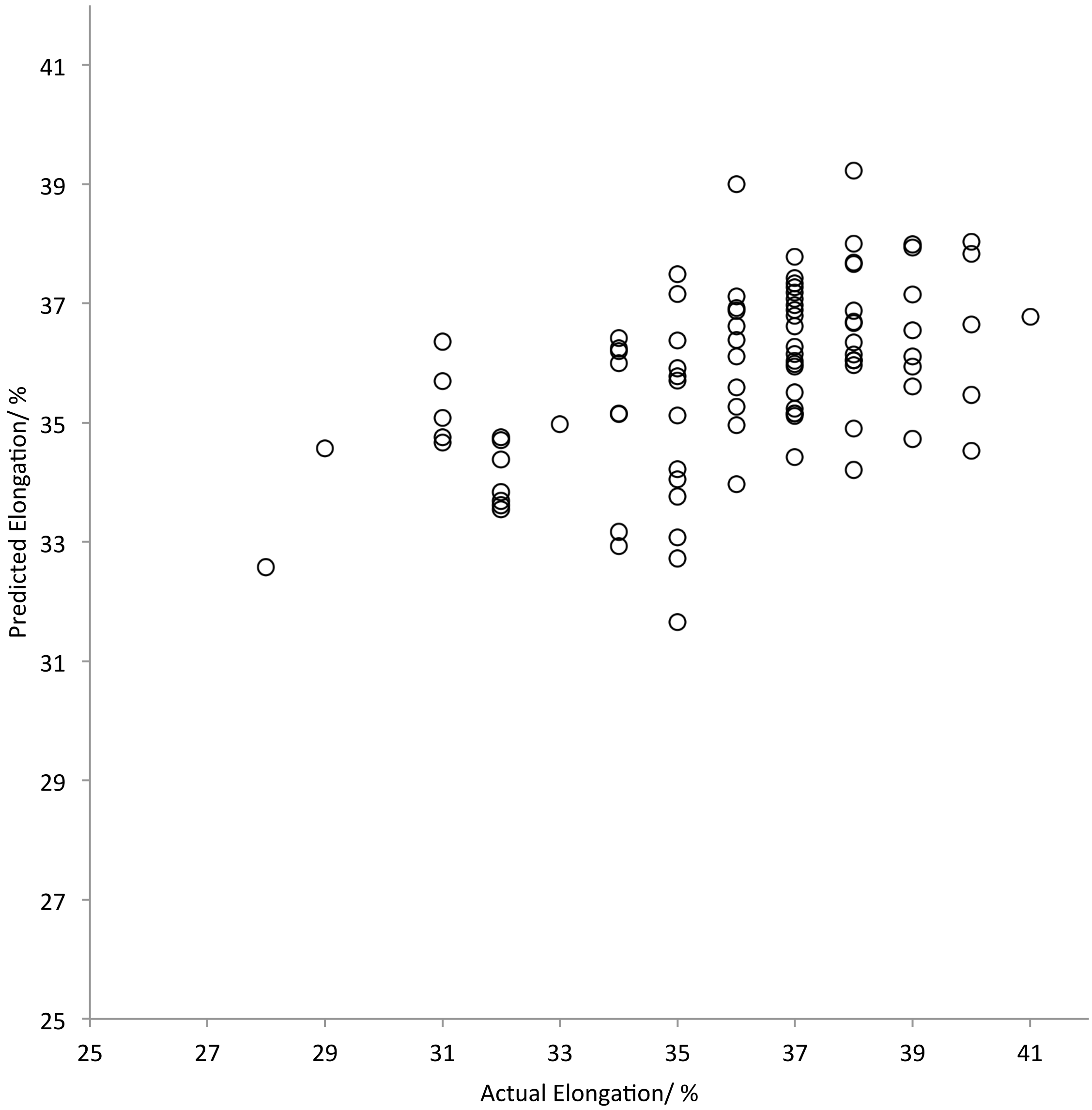


Figure 5.25: Actual elongation values against elongation values predicted by a generalised regression model for DX51 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the elongation model was found to be 1.3877. The following inputs were chosen:

Physical: gauge, width and length

Zodiac: direct fire temperature, radiant tube furnace start temperature, radiant tube furnace exit temperature, pot temperature, roll 30 temperature, coating weight, temper mill tension in, temper mill tension out and line speed

Hot Rolling: finishing temperature

Chemistry: carbon, silicon, sulphur, phosphorus, nickel, tin, niobium, boron, calcium and chromium

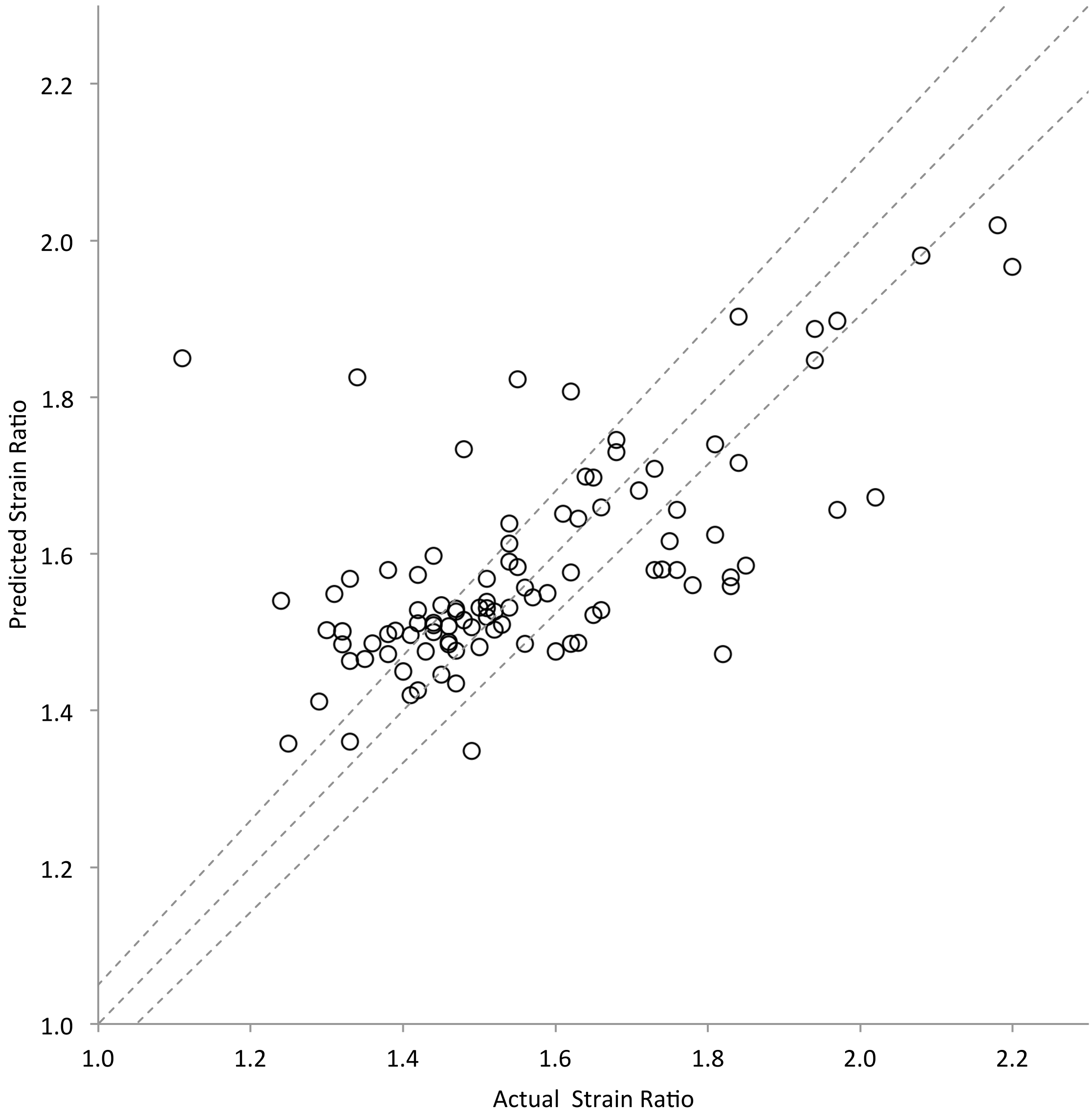


Figure 5.26: Actual strain ratio values against strain ratio values predicted by a generalised regression model for DX51 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain ratio model was found to be 1.2033. The following inputs were chosen:

Physical: length and cold reduction

Zodiac: direct fire temperature, radiant tube furnace start temperature, radiant tube furnace exit temperature, pot temperature, roll 30 temperature, water quench temperature, temper mill tension in, temper mill tension out, temper mill extension and coating weight

Hot Rolling: drop temperature, rougher temperature and finishing temperature

Chemistry: phosphorus, manganese, tin, nitrogen, aluminium (total), aluminium (soluble) and chromium

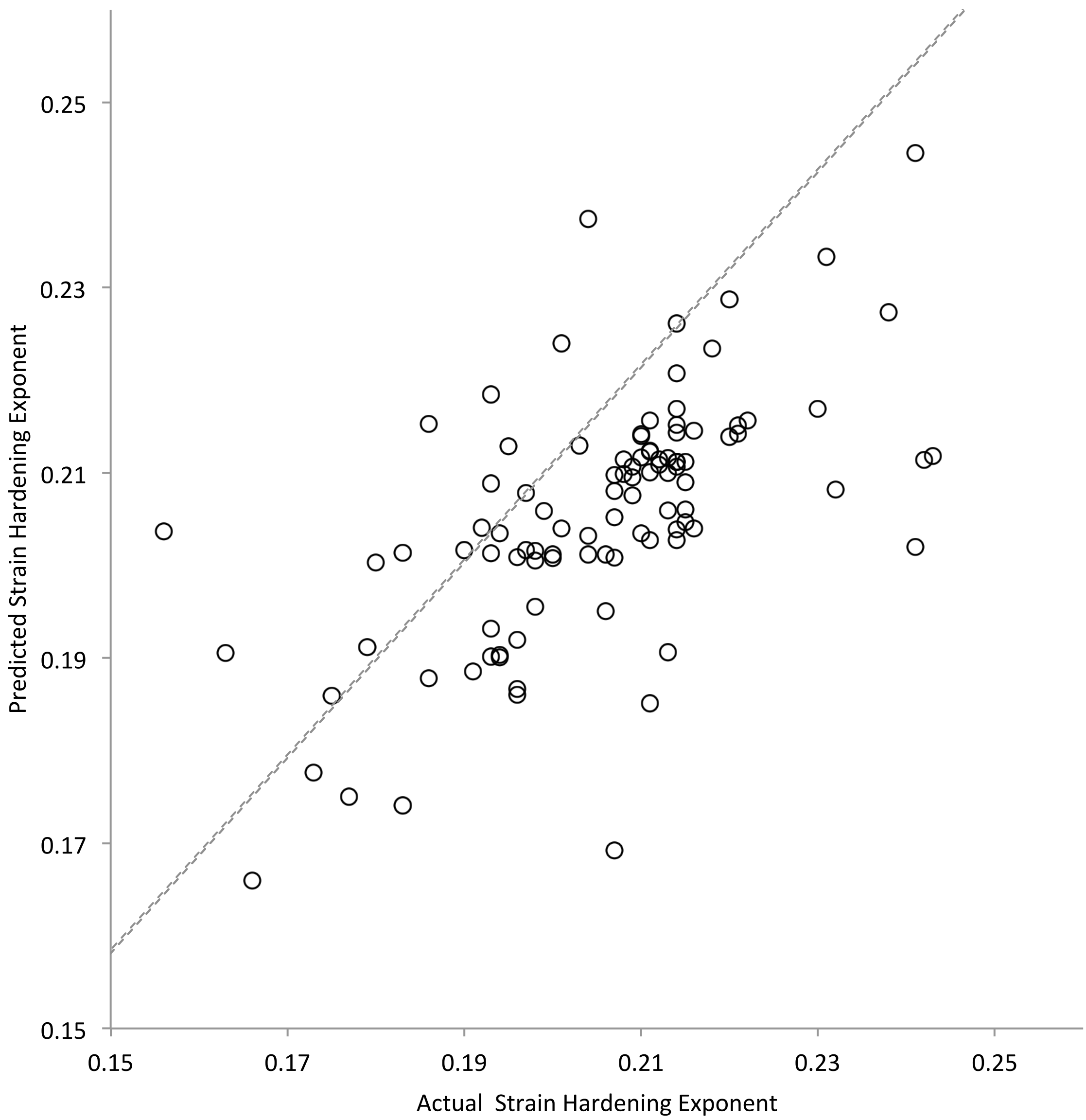


Figure 5.27: Actual strain hardening exponent values against strain hardening exponent values predicted by a generalised regression model for DX51 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain hardening exponent model was found to be 0.7271. The following inputs were chosen:

Physical: gauge, length and cold reduction

Zodiac: radiant tube furnace start temperature, snout temperature, roll 30 temperature, water quench temperature, temper mill tension in, temper mill tension out, temper mill extension, coating weight and line speed

Hot Rolling:

Chemistry: carbon manganese, tin, nitrogen and titanium excess

Table 5.7: Statistical data produced from validation data set from a generalised regression model of DX51 steels meeting specification trained using a genetic algorithm and constant spread value

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	25.7	5.1	1.04%	0.88
Proof stress	118.3	10.9	2.86%	0.80
Elongation	8.671	2.94	6.34%	0.54
Strain ratio	0.026	0.16	7.49%	0.64
Strain hardening exponent	0.00017	0.013	4.41%	0.61

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

The results achieved for the DX51 steels show that there is a strong case for furthering the modelling of these steels using the generalised regression method. The ultimate tensile strength and proof stress predictions are similar to those obtained predicting the properties of steels produced via the CAPL at Port Talbot, however they fail to match those for other steels produced at Llanwern. It is likely that this discrepancy is due to the size of the data set used to make the models, with the available DX51 data set being a similar size to the ones used for the CAPL models. The modelling technique failed to produce accurate predictions for the strain hardening exponent, r-value and elongation. Elongation continues to be an issue across the range of steels studied for this project, so the failure to predict it for DX51 steels was not surprising. The models of DX51 steels produced on Zodiac compared favourably to the models of the similar DC01/03/04 steels produced on CAPL. This result further highlighted the assumed discrepancy between the quality of data from the two lines.

The results from the SD350/450 models are shown in Figures 5.28 and 5.29. Due to the incompatibilities of the data set with the importing tool mentioned above only the ultimate tensile strength and proof stress were modelled. Statistical data about these results is given in Table 5.8. As before, lines representing where the predicted value equals the actual value as well as ±5% error lines have been superimposed on to these results.

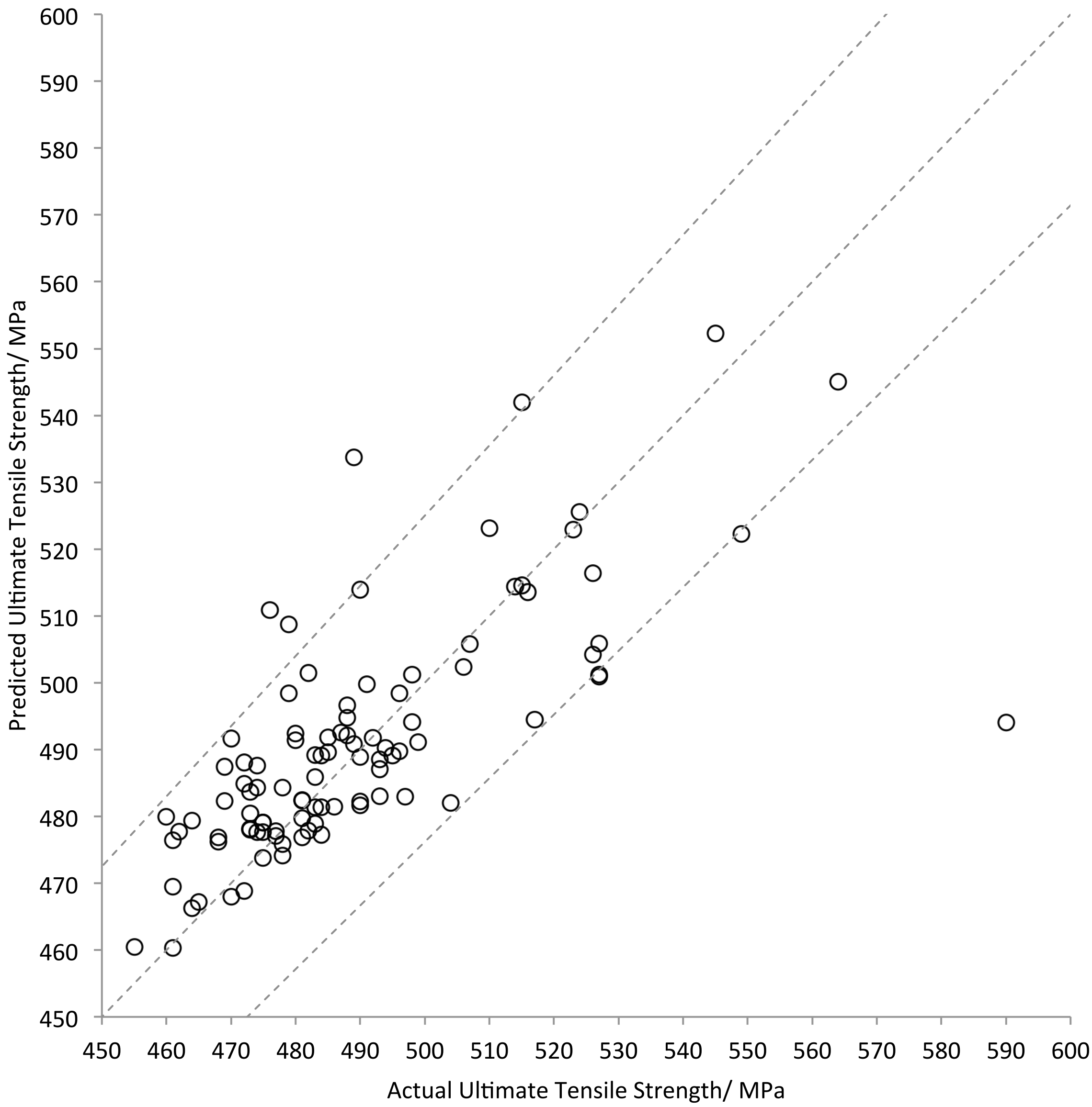


Figure 5.28: Actual ultimate tensile strength values against ultimate tensile strength values predicted by a generalised regression model for SD350/450 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the ultimate tensile strength model was found to be 1.4780. The following inputs were chosen:

Physical: weight, width and length

Zodiac: direct fire temperature, radiant tube furnace start temperature, radiant tube furnace exit temperature, snout temperature, pot temperature, temper mill tension in, temper mill tension out and temper mill elongation

Hot Rolling: drop temperature, rougher temperature and coiling temperature

Chemistry: carbon, sulphur, phosphorus, manganese, copper tin, nitrogen, aluminium (total), niobium, boron, titanium, calcium and molybdenum

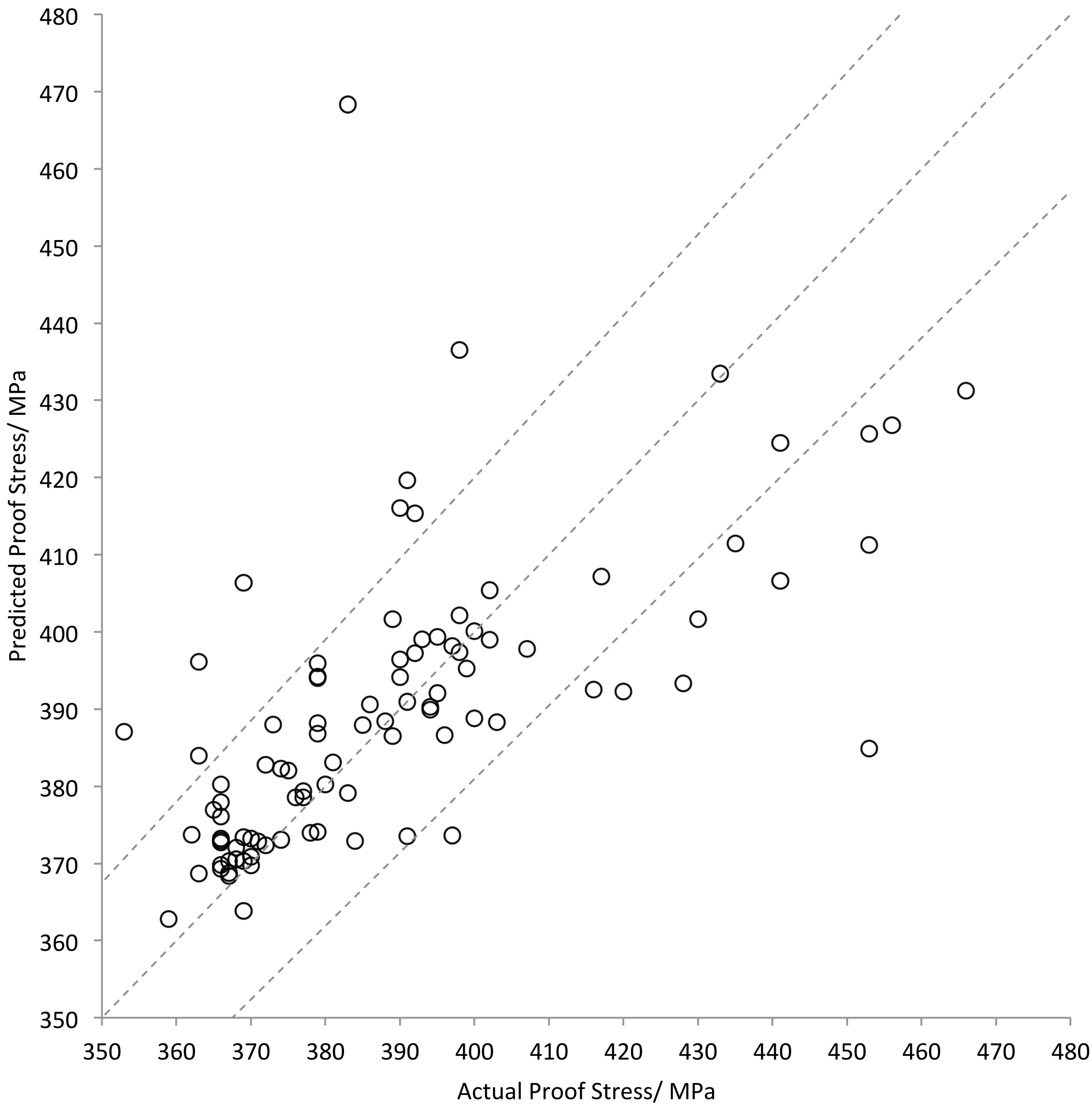


Figure 5.29: Actual proof stress values against proof stress values predicted by a generalised regression model for SD350/450 steels meeting specification trained using a genetic algorithm and constant spread value (Dashed lines represent where the predicted value equals the actual value as well as ±5% error)

The optimised spread value for the strain hardening exponent model was found to be 0.9220. The following inputs were chosen:

Physical:	width and length
Zodiac:	direct fire temperature, snout temperature, pot temperature, temper mill tension in, temper mill elongation and line speed
Hot Rolling:	rougher temperature
Chemistry:	silicon, nickel, vanadium, aluminium (soluble), molybdenum, calcium and boron

Table 5.8: Statistical data produced from validation data set from a generalised regression model of SD350/450 steels meeting specification trained using a genetic algorithm and constant spread value

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	2809.2	53.0	3.26%	0.28
Proof stress	862.4	29.4	4.09%	0.60

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Closer inspection of the results concerning the ultimate tensile strength predictions indicated that there were two anomalous results. The one prediction related to the actual value being considerably higher than would be expected. The second occurred when the model had failed to produce a prediction. Referring back to Table 5.6 it is clear to see that these excessive values exist in the proof stress data as well. Issue relating them have failed to materialise as they were part of the modelling data rather than training of validation data. The offending results were removed and the calculations repeated. These results are shown in Table 5.9.

Table 5.9: Revised statistical data produced from validation data set from a generalised regression model of SD350/450 steels meeting specification trained using a genetic algorithm and constant spread value

Property	MSE	RMSE	MPE	R
Ultimate tensile strength	254.5	16.0	2.03%	0.72
Proof stress	862.4	29.4	4.09%	0.60

MSE: Mean square error; RMSE: Root mean square error; MPE: Mean percentage error; R: Correlation

Using the current modelling technique the first impression one gets of the accuracy of a model is through its mean square error, as the change is constantly reported. Models that predict well (i.e. have a low error) can easily be spotted as the value can be seen. Normally a high error value indicates that model is struggling to simulate the process. It was with this in mind that it was initially felt that models for the SD350/450 grades were producing poor predictions as their error values were large. Upon plotting the predictions from the model it was clear to see that this was not necessarily the case. The ultimate tensile strength prediction mainly fell within the target band. There were two anomalous results that had a large effect the error.

The first of these was a null prediction; the model was unable to produce a prediction for that coil as its processing was so different to any coils it had seen before. If this case were to be encountered in a real life situation it would not cause any problems other than that coil requiring a physical test to ascertain its properties. The second of these occurred when the actual ultimate tensile strength value recorded for that coil was significantly higher than any other coil in the data set (around 700MPa). The model predicted this coil to have a value closer to the other coils in its history, causing a large error. This example could not be easily identified if the model were in actual use, as the predicted value was valid. Hopefully the other properties would highlight an issue with this coil. It may also be that the actual value recorded was erroneous.

For the proof stress predictions the large error was not as easy to explain. Looking at the results in Figure 5.29 it can be seen that for many of the lower values of proof stress the predictions were quite accurate. Also there appears to be more coils with values in this area. For larger values of proof stress the predictions are less accurate. It is again likely that the size of the data set used to create the model has led to this error. Whilst there are enough examples of coils with lower proof stress values for the model to make predictions, there are not enough at the higher end of the scale, thus the model struggles. A large data set would most likely decrease the error for these higher proof stress coils, whilst the accuracy of the predictions for lower proof stress values would also increase, meaning that the observed discrepancy would remain.

5.5. Conclusions

In this chapter a genetic algorithm was combined with the previously developed generalised regression approach in an attempt to increase the predictive accuracy of models of continuous annealed steels. Two different approaches were put forward; one using a constant spread value for all iterations and the other varying the spread for each iteration. Both approaches were shown to have a positive influence on some of the properties, but training times were increased dramatically. Upon comparison of the results from the two different approaches it was determined that the constant spread approach was the most suitable as it offered a higher accuracy with less impact on the training time.

The comparison was carried out using the 3004/05 steels produced on Zodiac. For these grades the training routine was able to develop models of the ultimate tensile strength, proof stress and strain hardening ratio that could be used to produce accurate predictions. The strain ratio results were not as good; however it was felt that this model could still find use as a method of analysing the relationships that relate to this property. As with previous attempts the elongation value proved difficult to predict and little improvement was gained using this approach. The inputs chosen by the genetic algorithm were comparable with the factors known to affect the properties under investigation.

With a fully developed model training routine the properties of other grades were also predicted. Again the strength values proved easier to predict than the other properties and elongation remained a problem. The results obtained from these newly developed models were able to better those from all previous attempts. As well as models of grades already under consideration in this report two additional sets of grades produced on Zodiac were also modelled. One of these grades belonged to a different subset than any of those previously studied. Given the small number of coils available to model this grade the results suggest that the modelling approach can be extended to cover it.

These findings suggest that generalised regression network based models combined with a genetic algorithm are a suitable non-linear method for predicting many of the properties of annealed steels for all the grades under consideration. Inputs chose by the training routine mirror those factors that have been shown by other researchers to affect the properties of steel. This suggests that the developed models may be a suitable method to assess these relationships and possibly quantify them.

CHAPTER 6 – ANALYSIS OF PROCESSES USING THE DEVELOPED MODELS

6.1. Introduction

An important part of this work is to try and quantify the relationships that exist between the mechanical properties and process conditions so that the optimal process windows and scheduling tools can be developed. Quantifying these relationships is also a useful way of improving the transparency of any model. Whilst the principles behind the model may seem sensible and based on a reasonable assumption, currently all one sees are inputs going in and properties coming out. If the complex relationships that the model hides can be found and shown to equate to known relationships then the model has a much better chance of being accepted. Some level of transparency can be derived by the current state of the modelling process by comparing the inputs selected by the training routine with the inputs known to relate to that particular property. Whilst this approach is a good start to the process, it is not detailed enough to meet the needs of this project and further quantification is needed.

It was with this in mind that a method of analysing the relationships that exist between the predicted mechanical properties and different process conditions was developed. It was believed that if it could be shown that the model was replicating mechanisms that had been identified by other research then another method of proving the reliability would exist, rather than just relying on the accuracy of its predictions. As an additional benefit the model may find use optimising the steel making process. Changes in mechanical properties can be related back to any changes in process conditions and any areas of potential optimisation identified. Another important aspect that needed to be considered was the effects of the variation of more than one process condition at a time.

6.2. Analysis of Single Inputs

A simple method of quantifying the relationships between properties and process conditions is to use a specifically constructed set of inputs which reflect the changes in the processes of interest. This process will vary by the required amount while all other processing conditions are held at a set value. This set of inputs can then be run through the model which predicts the required property. The model will evaluate this data in the same manner as if it was an actual coil, producing a predicted property. The predicted properties, or their variation from a mean value, can then be plotted against the change in the processing condition to illustrate any relationships that exist.

The operation of the models used in this project requires that data is normalised before it is introduced to the generalised regression network. The normalisation process uses the mean and standard deviation of the data set used to create the model. The result of this is that a value of zero entered into the actual network represents a process condition equal to the mean value of the training data. Non zero values indicate an actual process condition of that number of standard deviations above or below the mean. This allowed a simple method of coding to be developed so that the sensitivity analysis could be run quickly. This method relies on several iterations with all but one process condition held at a set value; either the mean (zero) or a number value representing that number of standard deviations above or below the mean. The target process condition is then varied from three increments below the set value to three increments above. The value of these increments can be altered and represents a number of standard deviations. The target value is then to be the next process condition and this repeats until all the inputs to the model have been targeted. An example of one of these data sets is shown in table 6.1.

Table 6.1: Example data set for single input analysis model

		Iteration													
		1	2	3	4	5	6	7	8	9	10	11	12	13	...
Input State	Gauge	0	-3	-2	-1	1	2	3	0	0	0	0	0	0	...
	Width	0	0	0	0	0	0	0	-3	-2	-1	1	2	3	...
	RTF start	0	0	0	0	0	0	0	0	0	0	0	0	0	...
	Soak Temp	0	0	0	0	0	0	0	0	0	0	0	0	0	...
	Cold Reduction	0	0	0	0	0	0	0	0	0	0	0	0	0	...
	Carbon	0	0	0	0	0	0	0	0	0	0	0	0	0	...
	Silicon	0	0	0	0	0	0	0	0	0	0	0	0	0	...
	Titanium	0	0	0	0	0	0	0	0	0	0	0	0	0	...

The creation of these data sets and their use with the required model was carried out using Matlab. This produced an output data set containing the seven predicted properties for each input along with that inputs mean and standard deviation. This data was then exported into a specific macro enabled Microsoft Excel worksheet. The base value, number of increments and property under investigation could then all be entered in to the work sheet and the macro used to quickly produce plots of the relationships.

6.2.1. Strain Ratio Investigation

The initial work focused on analysing the relationships that existed between the processing parameters and the strain ratio; with the Zodiac 3004/05 steels being evaluated first. This property was chosen as it is a key specification that customers require and according to plant operators is one of the properties that coils will routinely fail on. For the initial analysis all variables were held at the mean value, zero in the data set, with one variable changing by one standard deviation, between minus three and plus three. The results were then plotted as the range of the changing variable against the change in the property from the value produced using mean values only. In some cases the variation in a value would result in a negative value, which is not possible in real life. In these cases values from zero and above were plotted. Figure 6.1 shows the predicted effect of increasing the amount of cold reduction.

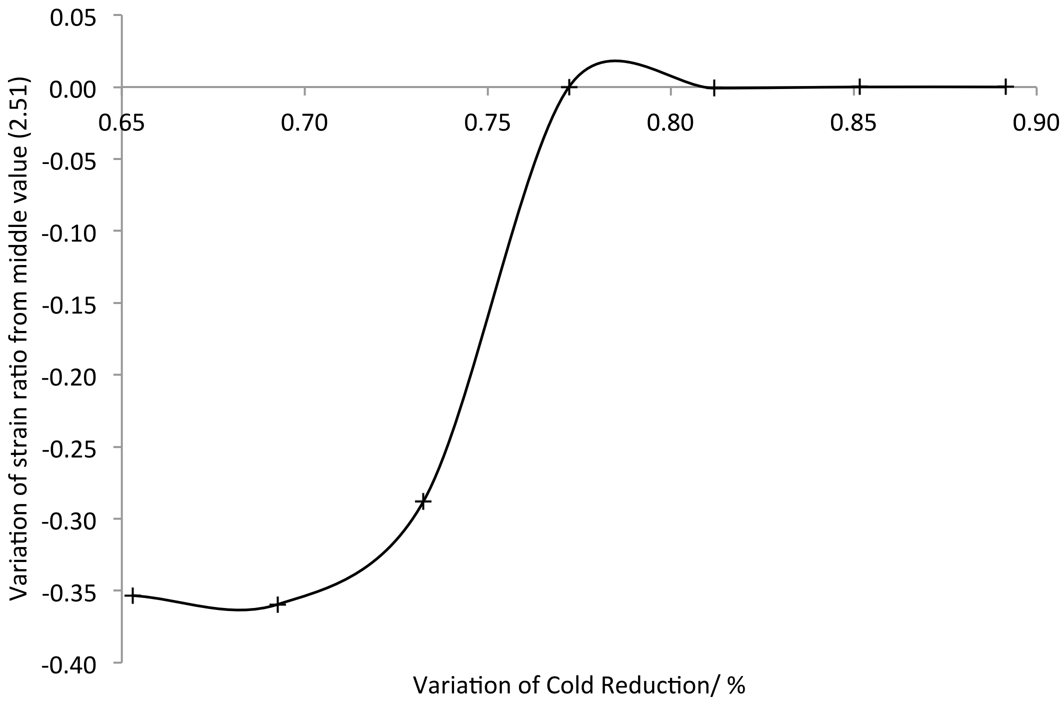


Figure 6.1: Predicted change in strain ratio based on the variation in cold reduction for 3004/3005 steels (holding other values at their mean)

In general, this result agrees with published data [32, 35] relating the cold reduction to the strain ratio, showing an increase in the amount of cold reduction leading to an increase in the strain ratio. The magnitude of the increase does not match that observed in actual steels [32], however this greater increase was also attributed to the soak temperature, which is not considered in this model. The increase observed in the actual tests appeared to have a more linear relationship and did not plateau at higher cold reduction values.

The same relationship was examined with the other model inputs being held at one standard deviation above and below the mean. These results are shown in Figures 6.2 and 6.3 respectively.

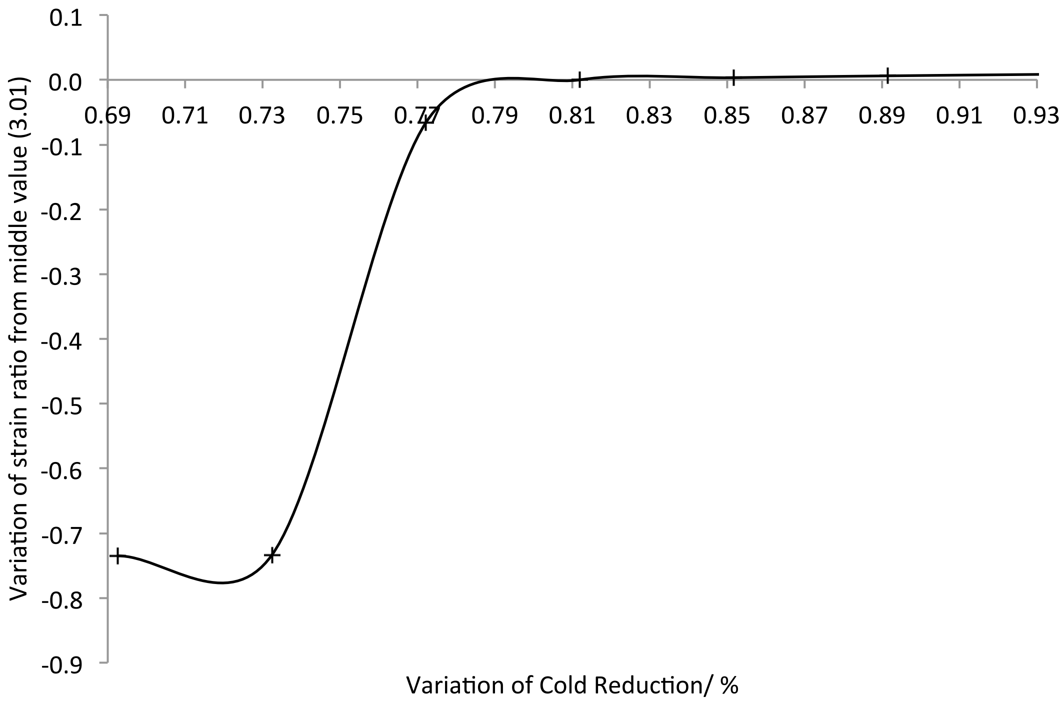


Figure 6.2: Predicted change in strain ratio based on the variation in cold reduction for 3004/3005 steels (holding other values at one standard deviation above their mean)

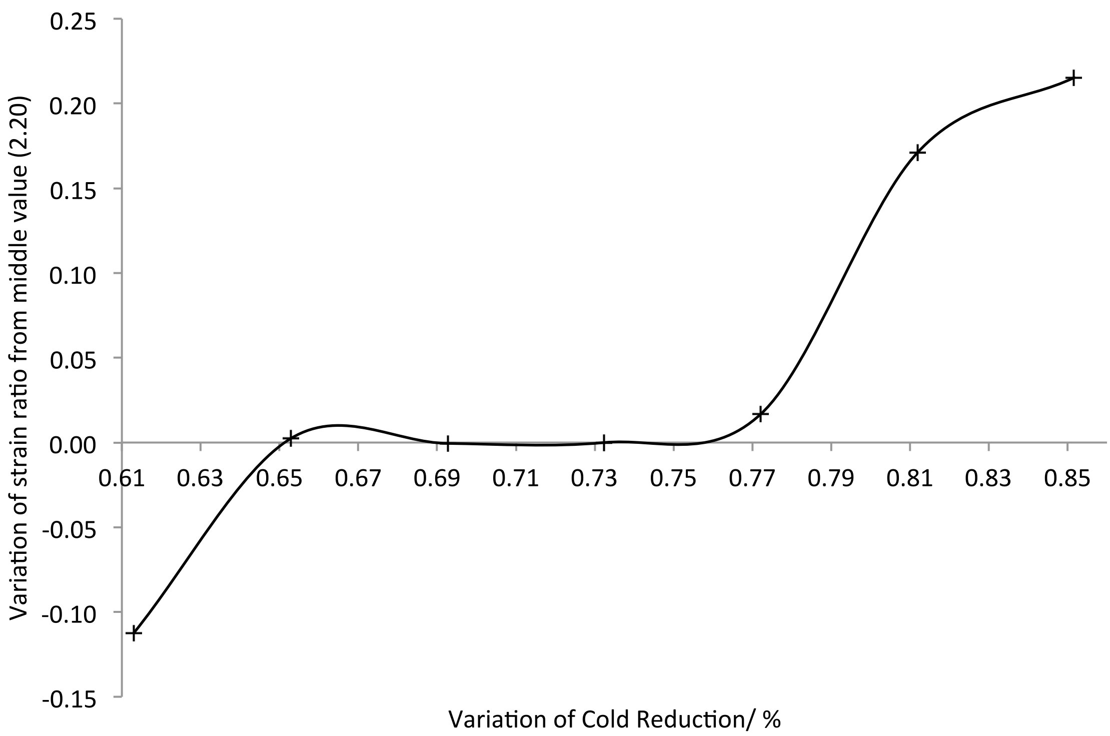


Figure 6.3: Predicted change in strain ratio based on the variation in cold reduction for 3004/3005 steels (holding other values at one standard deviation below their mean)

These results again show the increase in strain ratio relating to an increase in the cold reduction. With the other model inputs held at higher values (Figure 6.2), the same increase in cold reduction, from 70% to 80%, is seen to have almost twice the impact compared with the results shown in Figure 6.1. Again, a plateau is reached once the amount of cold reduction reaches 80%. Using lower inputs (Figure 6.3) creates an interesting pattern of results. Whilst the strain ratio increases for cold reduction values between 61% and 66% it then remains constant until about 76%, at which point it rises again at a similar rate as before. This rise continues for the remainder of the plot. The sudden stop in the increase is unlikely to be truly representative of the annealing process. It may be related to the fundamental principles of the model; one entry in the training data set matches these conditions very closely and therefore has a larger leverage.

The plateau effect observed in Figures 6.1 and 6.2 can be explained by examining the physical constraints of the actual process. The other inputs to these models are either set to the mean values or one standard deviation above. As the gauge is one of the inputs to this model, it means that this will be set to a reasonably high value for both these figures. The actual process may not be able to produce these grades using the high levels of cold reduction. This theory can be extended to the results in Figure 6.3. The continued increase in strain ratio for cold reduction values greater than 80% indicates that the cold mill is able to achieve these levels of cold reduction on gauges one standard deviation below the mean value.

The amount of cold reduction employed was also one of the inputs chosen to predict the strain ratio for the final model of DC05/06 coils. As a comparison the same method was applied to this model, with other values held at their mean and a variation of one standard deviation. The results of this simulation are shown in Figure 6.4.

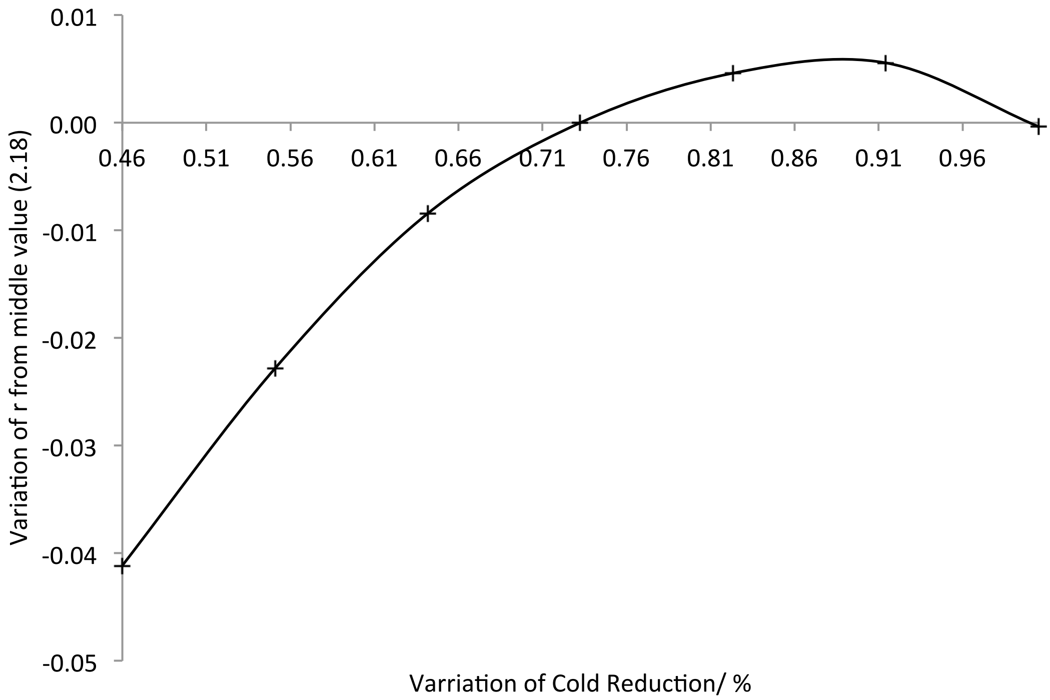


Figure 6.4: Predicted change in strain ratio based on the variation in cold reduction for DC05/06 steels (holding other values at their mean)

As with the 3004/05 steels an increase in the strain ratio was observed as the amount of cold reduction increased. The increase continues to a reduction value of around 90% after which a drop in strain ratio is observed. The increase in the strain ratio was considerably smaller than that observed for the other steel grades and results reported by other researchers. The shape of the curve was also different. The difference between the models of the different steels perhaps offers an insight into the different predictive capabilities of them both. While not perfect the 3004/05 model produced better predictions than its DC05/06 counterpart. This investigation has shown that the later model does not represent the actual process as accurately as the other model.

Another important factor which contributes to the formability of these grades is the carbon value. Ono et al (cited in [5]) investigated the effects of carbon contents on the properties of continuous annealed strip. Their work found that the decreasing the carbon content increased the strain ratio, with the increase reaching at plateau at 0.02% and below. The effect of carbon content on the strain ratio for 3004/05 steels was simulated, with the results shown in Figure 6.5 The simulation varied the carbon content between minus six and plus six standard deviations from the mean carbon value, other values were held at their mean. This larger range was used so that the focus was on the target value, 0.02%.

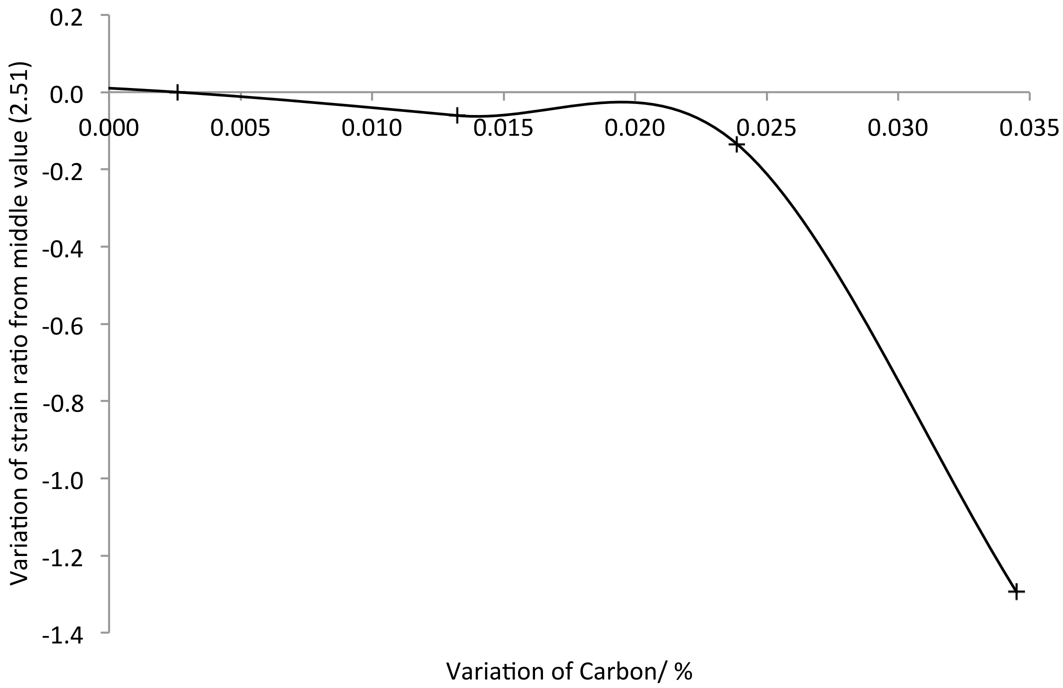


Figure 6.5: Predicted change in strain ratio based on the variation in carbon content for 3004/3005 steels (holding other values at their mean)

Again the predicted results were found to be in agreement with the literature. Increasing the carbon content up to a value of 0.02% appeared to have little influence on the predicted strain ratio. Once the carbon content rose above this value the strain ratio was seen to fall. The rate that the strain ratio falls is considerably greater than that observed in the literature and again may be a feature of the data set used to create the model. Attempts were also made to predict the effect of carbon content on the strain ratio when the other model inputs were held at values above and below their mean values. When the inputs were held at one standard deviation below their mean values the carbon content was seen to have no effect on the strain ratio. With the inputs one standard deviation above their mean values a trend similar to that in Figure 6.5 was produced. This time the strain ratio began to decrease when the carbon content was 0.025%. The decrease was much quicker, with the strain ratio value predicted to have fallen by three units in the range investigated, an unlikely result.

The same relationship was simulated using the DC05/06 model. Due to differences in the range of data used to make this model the carbon value was varied between minus three and plus three standard deviations. Other values were again held at their mean. The results of this simulation are shown in Figure 6.6.

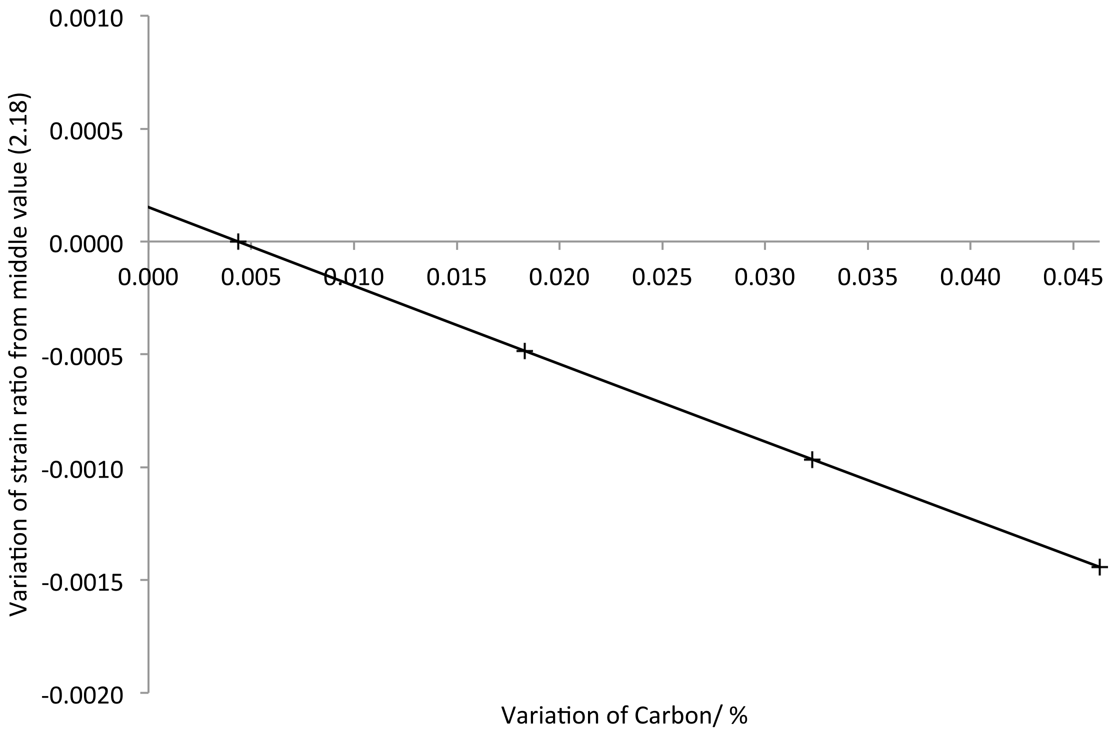


Figure 6.6: Predicted change in strain ratio based on the variation in carbon content for DC05/06 steels (holding other values at their mean)

The DC05/06 simulation of the effect of carbon content on strain ratio did not reflect a similar pattern to the results observed from the 3004/05 simulation or the available literature. A linear relationship was produced, with the strain ratio falling as the carbon content increase. The reduction in strain ratio was very small. These results highlight once again that the DC05/06 model does not represent the annealing process as well as the 3004/05 model. The range over which the simulation is carried out gives an indication as to some of the reasons for this difficulty. The range of standard deviations used to produce the DC05/06 strain ratio simulation covered carbon contents from 0% through to 0.045%. This was greater than the 3004/05 simulation range of 0% to 0.035% even though the simulation used only half the number of standard deviations. Similarly the range of cold reduction values was larger for the DC05/06 simulation. This may indicate that there are more outlying data points in this data set, another reason why models of this grade of steel failed to meet the accuracy of the 3004/05 steels.

6.2.2. Strength Relationship Analysis

The inputs affecting the strength of the steels under investigation were also analysed. Solid solution strengthening has already been identified as one of the factors that may have an influence on the final strength of steel. The sensitivity analysis method was used to assess the influence of the levels of phosphorus, silicon and manganese as well as carbon on the tensile strength as predicted by the ultimate tensile strength model of the DX51 steel. The results of this study are shown in Figure 6.7.

The predicted results show some agreement with research carried out by Evans et al [32], whose research into similar grades of steel found that all four alloying additions had a positive influence on this property. The previous study found that phosphorus had the largest effect on the strength, a result that the predictions appear to agree with. Silicon was predicted to have a greater effect than manganese, based on extrapolating the data in Figure 6.7. This result again agreed with the previous study, thought the shapes of the relationships differed. The results from Evans et al proposed a linear relationship between the phosphorus and silicon contents and the ultimate tensile strength. Their work suggests that the effect of the manganese content dismissed with increasing percentages. As with the strain ratio predictions the predicted change in property (the ultimate tensile strength) was found to be much less than the changes found in the literature.

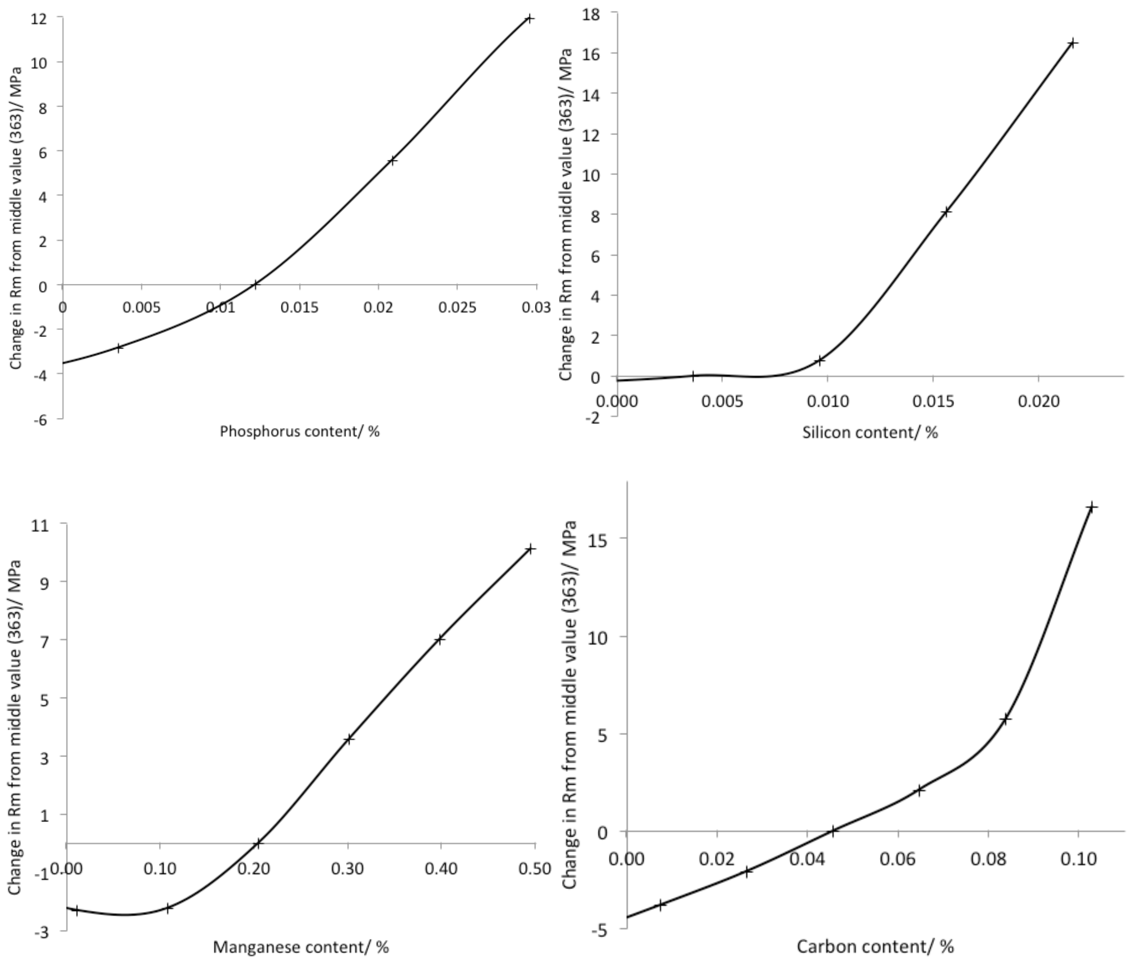


Figure 6.7: Predicted variation in the ultimate tensile strength of DX51 steels from a base value of 363MPa due to changes in carbon, phosphorus, manganese and silicon content

A direct comparison between the DX51 models of steels produced on Zodiac and the DC01/03/04 models of steels produced on CAPL could not be carried out as the later models did not use the amount of phosphorus, silicon or carbon as inputs. However the manganese content was used and the predicted effects of this on the ultimate tensile strength of DC01/03/04 steels is shown in Figure 6.8.

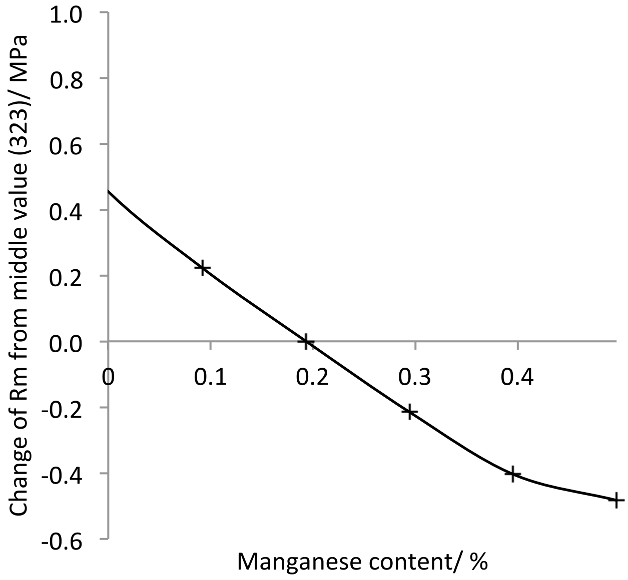


Figure 6.8: Predicted variation in the ultimate tensile strength of DC01/03/04 steels from a base value of 323MPa due to changes in manganese content

Unlike the DX51 predictions the predicted relationship between manganese content and the ultimate tensile strength of DC01/03/04 steels was found not to agree with the expected results as found in the available literature. An increase in the amount of manganese was seen to lower the strength. The rate of decrease was observed to change at manganese contents of 0.4% and above. It should be noted that the predicted range of this change in the ultimate tensile strength of the steel was very small, around 1MPa. The differences between this predicted relationship, the relationship predicted for the DX51 steels and results found in the literature may give an insight into the lower predictive accuracy of the CAPL model when compared to the Zodiac ones.

The effects of temper rolling were also analysed. During the modelling phase of this project it was observed that the temper rolling related processes were often selected as model inputs, normally with more than one process being selected. As stated in Chapter 2, temper rolling is employed to remove yield point elongation and control the surface quality of the strip. It is one of the final processes that a coil will undergo before exiting the mill. The yield point elongation phenomenon is caused by the load required to deform the material dropping at the onset of yielding, relate to an increase in the number of mobile dislocations. This results in a horizontal section on a stress-strain plot. Once the entire material has yielded the stress-strain curve rises in the normal way due to work hardening [26]. By applying a small amount of extension the temper roll removes this point, meaning that subsequent yielding will result in a smooth curve. The study by Evans et al considered the effects of temper rolling [32]; it found that increased temper rolling was found to have little effect on the ultimate tensile strength and a reduction in the proof stress. The predicted effects of temper rolling on the proof stress and ultimate tensile strength on the properties of DX51 and ultimate tensile strength of DC01/03/04 steels was investigated to see if it agreed with these findings. The predicted results are shown in Figures 6.9 and 6.10. Temper mill extension was not selected as input to the DC01/03/04 proof stress model so this analysis could not be carried out on that property.

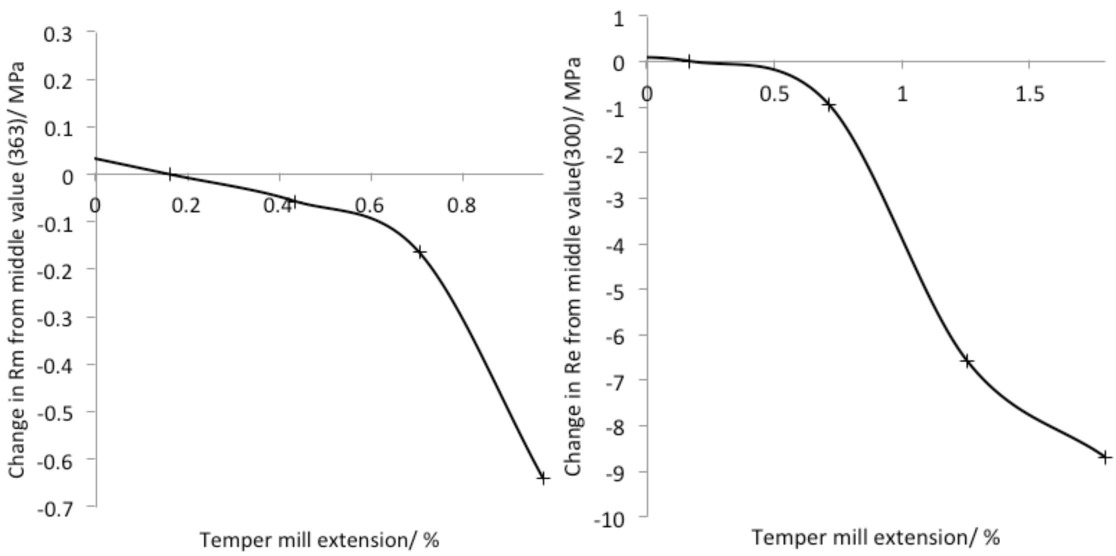


Figure 6.9: Predicted variation in the ultimate tensile strength and proof stress of DX51 steels due to changes in temper mill extension

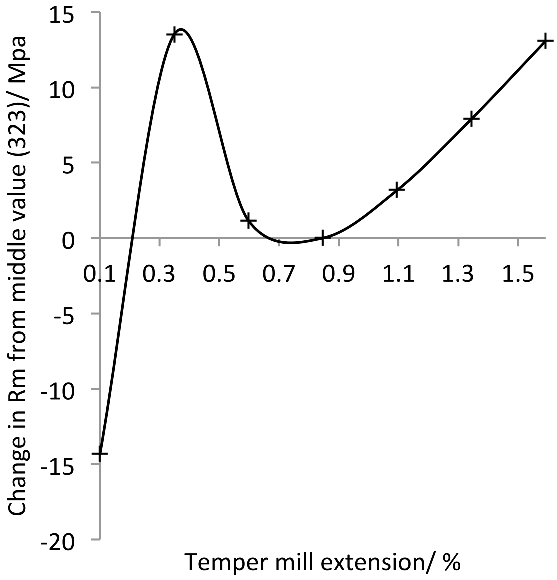


Figure 6.10: Predicted variation in the ultimate tensile strength of DC01/03/04 steels due to changes in temper mill extension

The findings in Figure 6.9 agree with the observations made in other research. An increased amount of temper mill elongation was seen to predict a decrease in the proof stress of DX51 steels. A predicted decrease was also observed in the ultimate tensile strength model; this decrease was much smaller than that predicted decrease in proof stress. Interestingly the predicted relationships between these strength values and the temper rolling exhibited very similar shapes, which is likely to be a result of the modelling process.

The predicted relationship between the ultimate tensile strength and temper mill extension of DC01/03/04 steels is completely different. The overall trend was an increase in ultimate tensile strength over the range of extension values. A rapid increase in strength was observed up to 0.3% extension with a reduction occurring between around 0.3% and 0.7% extension. After this the strength gradually rose again. An extension of 1.5% was predicted to increase the ultimate tensile strength by 30MPa, nearly 10% the middle value. This pattern is difficult to explain in terms of the physical process occurring within the steel and so must be attributed to the modelling process. For this grade of steel a mean value of 0.838% temper mill extension was applied with a standard deviation of 0.083%. Assuming that the amount of reduction was normally distributed this would mean that the majority of coils would have extension values between about 0.65% and 0.95%. At the extremes of the plot there would be very few coils, meaning that if the ultimate tensile strength recorded for these was significantly higher or lower than those centred on the mean they would have a much larger effect on the predicted relationship. With only a handful of data points at the extremes increases or decrease in strength due to other processing conditions do not get averaged out. As the sensitivity analysis is only focused on the one input it would consider a coil with a significantly different value of the property under investigation to have this value because of the input being focused on, rather than a variation in other process conditions. This example has shown why the results of the sensitivity analysis need to be considered carefully and that this approach cannot be used to extrapolate beyond the data used in the original model.

6.3. Multivariate Input Analysis

The original sensitivity analysis tool was developed to look at the effect of varying one process at a time on the predicted properties of steel. The ability to modify the central value around which process conditions were varied also added scope to see if any interaction effects were present. An interaction effect is when the change in one condition influences the relationship between another condition and the target property. This method was somewhat crude as all variables were modified, meaning that the presence of an interaction effect could be identified but the cause could not. An example of this is the relationship between the strain ratio and amount of cold reduction investigated previously in this chapter. Figure 6.2 shows the relationship with the central value held at one standard deviation above the mean, Figure 6.3 shows this with the central value one standard deviation above the mean. While a difference can clearly be seen between the two relationships there is no way of telling what has caused this. It might be an interaction effect, in which case one has no idea what property is causing this, or it might an anomaly in the data set.

For this reason an alternative method of analysing any interaction effects was developed. This method used similar principles to those used to produce the initial sensitivity model. The main property under investigation was varied by one step above and below the central value, again by a multiple of the standard deviation. Possible interaction effects were observed by also varying another input value between two states; high, one standard deviation above the central value, and low, one standard deviation below. Those values not under investigation were again held at the central value. An example of a simple input set up is shown in Table 6.2.

Table 6.2: Example data set for multivariate input analysis model, gauge is the main value under investigation (Key: H – high, L – low, 0 – central)

		Iteration														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Input State	Gauge	0	**H**	*L*	0	**H**	*L*	0	**H**	*L*	0	**H**	*L*	0	**H**	*L*
	Temperature	0	0	0	**H**	**H**	**H**	*L*	*L*	*L*	0	0	0	0	0	0
	Cold Reduction	0	0	0	0	0	0	0	0	0	**H**	**H**	**H**	*L*	*L*	*L*

Predicted relationships were produced using the methods details above for 3004/5 steels produced on the Zodiac Line at Tata's Llanwern plant. The model predicting the strain ratio was analysed, as it had previously been shown that for lower values an unusual relationship was present (see Figure 6.3). The new sensitivity analysis method produced results in a slightly different way to the previous method. For comparison purposes the predicted relationship between just the amount of cold reduction and strain ratio using the new methodology is shown in Figure 6.11.

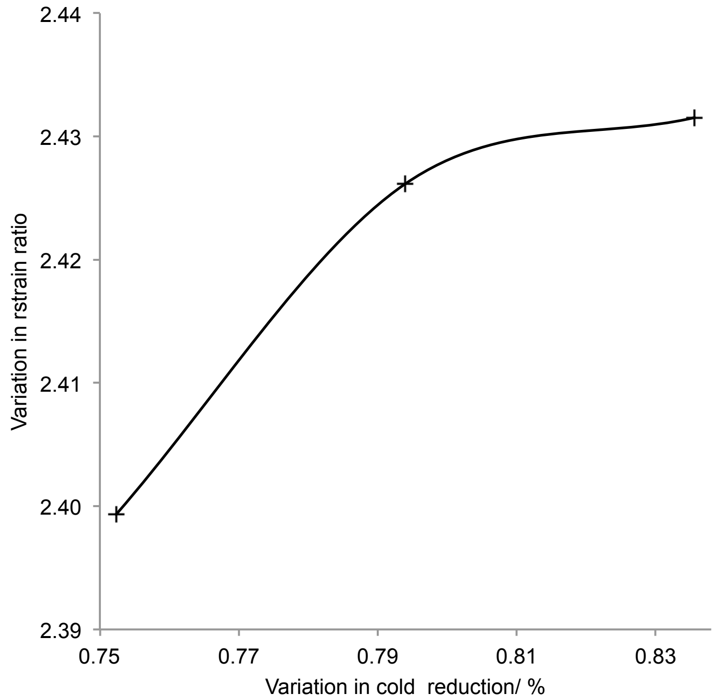


Figure 6.11: Predicted variation in strain ratio based on change in cold reduction for 3004/05 steels

The first test of the new sensitivity analysis method investigated the interaction between the amount of cold reduction employed and the carbon content on the strain ratio predictions. This relationship was chosen as the both inputs had been looked at individually using the previous method and were found to closely match the actual relationships reported by other researchers. Based on those results it was assumed that predict strain ratio would increase with the amount of cold reduction employed, with the carbon content having little effect on this relationship providing that it was below 0.02%. The results of this investigation are shown in Figure 6.12.

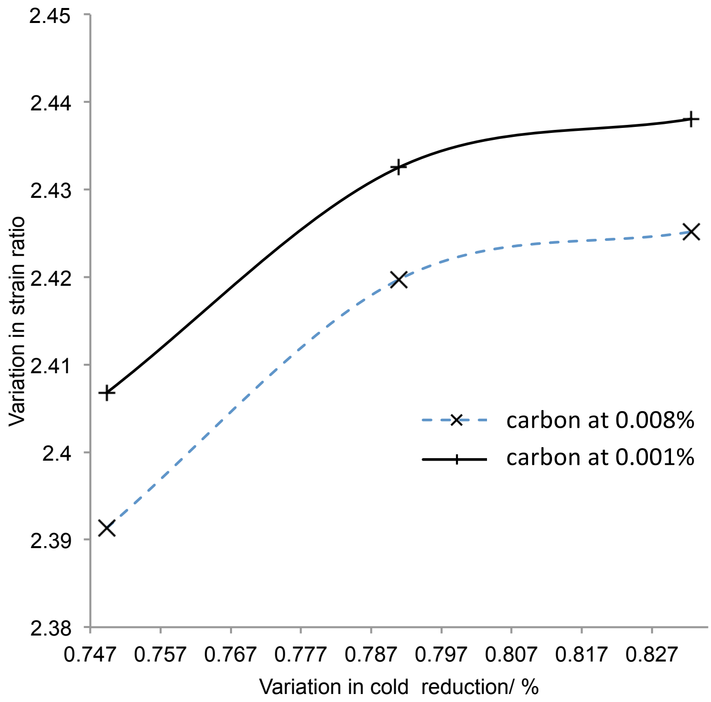


Figure 6.12: Predicted variation in strain ratio based on change in cold reduction for 3004/05 steels with differing carbon contents

An increase in the amount of cold reduction was seen to an increase the strain ratio, matching the relationship shown in Figure 6.11. Whilst this result adhered to the expected outcome the effect of the carbon content did not. An increase in the carbon content gave rise to a slight decrease in the strain ratio. This decrease is uniform along the range of cold reduction studied. This reduction in strain ratio for higher carbon values can be explained by the slight gradient of the relationship at the appropriate values shown in Figure 6.5. The traces for the different carbon values in Figure 6.12 run parallel to each other, showing that there is no interaction effect between this and the amount of cold reduction.

Next the effect of the line speed on the relationship between cold reduction and strain ratio was predicted. Again the same 3004/05 grades steels were analysed. These results are shown in Figure 6.13.

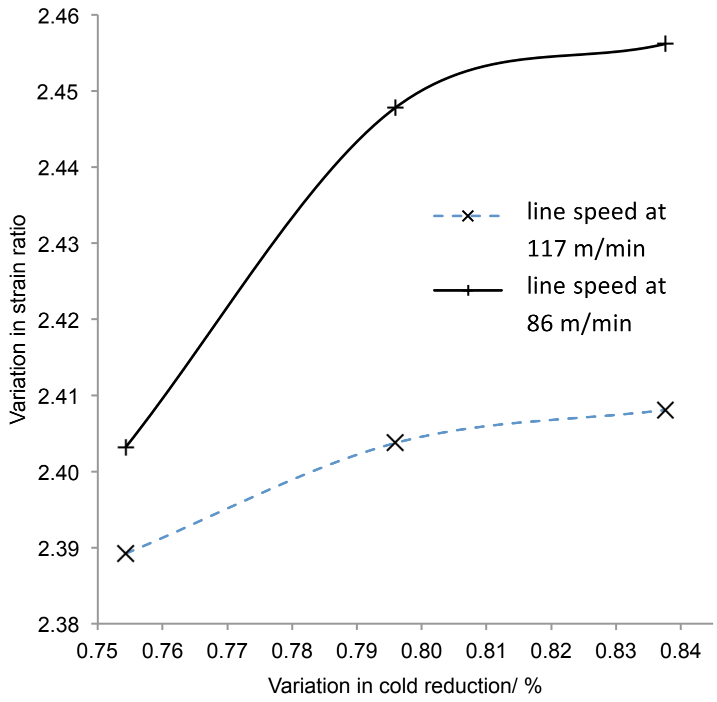


Figure 6.13: Predicted variation in strain ratio based on change in cold reduction for 3004/05 steels annealed at different line speeds

The line speed can be directly related to the soak and annealing times. Running the line at a slower speed means that these times will be longer. Longer soak times aid recrystallization and promote grain growth after it is complete. This leads to an increase in the {111} texture and a better r-value [32]. This relationship was discussed in Chapter 2 and an illustration of it is shown in Figure 2.13. During cold rolling the microstructure is heavily deformed, with the grains present after hot rolling being stretched and distorted. The material is work hardened, more deformation leads to more stored energy within the material. It is this stored energy that provides the driving force for recrystallization to occur. The recrystallization temperature is affected by the size of grains, as grain boundaries are a preferential site for nucleation to occur. Smaller grains prior to annealing means that there are more grain boundaries and hence the recrystallization temperature is lower [15].

The predicted relationship shown in Figure 6.13 assumes that all other inputs are held at a constant level. This means that prior to annealing both strips with either level of line speed have the potential to reach the same strain ratio for any given amount of cold reduction. It is also important to note that this means the annealing temperature is assumed to be the same in both circumstances. Once annealing has started the differences in line speed leads to the discrepancies between the two levels stacking up.

The first of these will relate to the heating of the strip. Running the line at a quicker speed would normally require the temperature to be higher or a thinner gauge in order for the correct temperature to have penetrated the entire strip. As these inputs are in fact kept constant for the purposes of the model the theoretical temperature of the strip run at a higher line speed will be lower than that of the strip run at a slower speed. The lower temperature may not be much higher than the required recrystallization temperature, reducing the rate at which this takes place. This is compounded by a longer annealing time decreases the recrystallization temperature [15].

The second issue is that the theoretical soak time for the strip annealed at a higher speed will be shorter than that of the slowly annealed strip. For strips at the same temperature this would mean that the final grain size would be smaller. As recrystallization will already take a longer time to occur the final grain size is likely to be even smaller. Conversely, the strip annealed at a slower line speed will have recrystallized at a higher rate and will have longer for grain growth to occur, resulting in a much greater discrepancy between the final strain ratios.

The overall effect of these two facts is that stored energy within the steel, caused by the cold rolling, cannot take full effect if the line speed is higher. Under normal conditions this energy will be able to drive the recrystallization as the strip will be hot enough and soak for a long enough time to allow this. The lower effectively increases the required temperature and reduces the soak time, meaning that the extra stored energy for greater amounts of cold reduction is not put to use. This is seen in the levelling off of the lower line in Figure 6.13. One important thing to note about these results is that combinations required to produce actual results like these are not likely to be employed. A strip run at a quicker line speed is likely to be annealed at a higher temperature. This highlights a potential problem with the modelling approach; possible interaction effects may in fact be due to other inputs not currently being analysed. For this reason care should be taken to correctly analyse any results.

An interesting relationship was found to exist between the hot rolling drop temperature and amount of cold reduction on the strain ratio. The predicted plots of this relationship are shown in Figure 6.14.

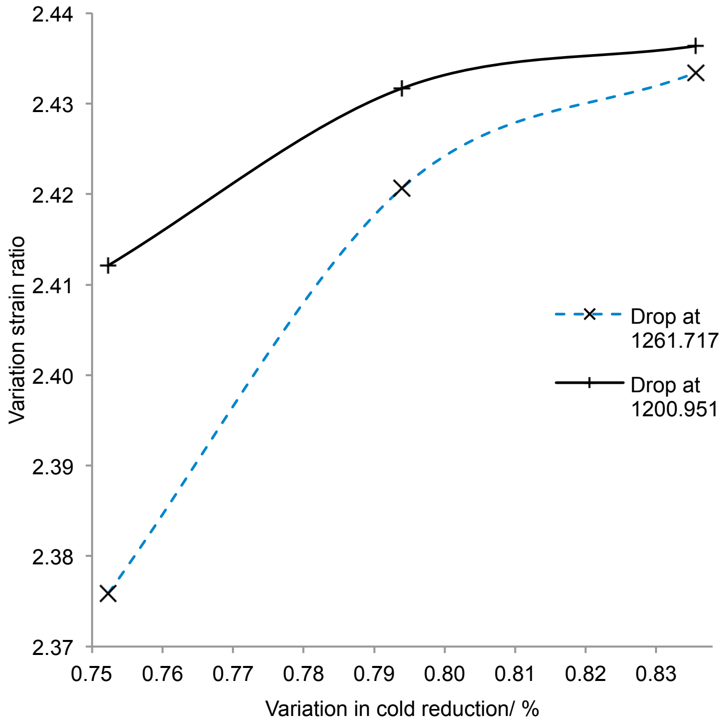


Figure 6.14: Predicted variation in strain ratio based on change in cold reduction for 3004/05 steels hot rolled with a different drop temperature

The relationships shown in Figure 6.14 show the expected result of strain ratio increasing with the amount of cold reduction. The strain ratio is predicted to be lower at all levels of cold reduction for steels produced with a lower hot rolling drop temperature. The discrepancy between the two temperatures reduces as the amount of cold reduction increases. The relationship between strain ratio and drop temperature can easily be explained by examining the differences between batch annealing and continuous annealing.

During the initial heating of batch annealed steels aluminium nitride precipitates on to the sub-grain boundaries. This inhibits the nucleation of new grains and leads to the production of larger grains [5]. In order for this to occur the aluminium and nitrogen must remain un-combined during the hot rolling process. One method of preventing them combining is to use a low coiling temperature (about 550^{o}C). Control of the drop (or reheat) temperature is also important; with higher temperatures required for batch annealed steels so that all aluminium nitride is dissolved [32].

Continuous annealing employs much quicker heating rates. Because of this there is not enough time for aluminium nitride to precipitate out. This results in the aluminium and nitrogen remaining in solution. The free nitrogen is detrimental to texture development within the steel and also leads to increased strengthening. In order to reduce the amount of free nitrogen in solid solution higher coiling temperatures are used for continuous annealed steels; giving time for aluminium nitride to precipitate while the coil is cooling. A lower reheat temperature can also be employed to prevent aluminium nitride being dissolved at this stage of the coils production [5, 32].

The interaction between the two varying processes is slightly harder to explain. Although the free nitrogen retards the rate of recrystallization it has been reported that it is not detrimental to the final grain size. Recrystallization is also a function of the annealing time and annealing temperature. Increased amounts of cold reduction leads to more stored energy within the steel, which leads to a reduction in the recrystallization temperature [32]. Referring back to Figure 6.14, at lower cold reduction rates the recrystallization temperature will be higher. If the drop temperature is higher (hence more free nitrogen) then the annealing furnace temperature and annealing time may be such that the effect of nitrogen is strong. With a lower drop temperature the annealing time and temperature may be sufficient to negate the effect of the free nitrogen. At higher amounts of cold reduction the recrystallization temperature will be lower, meaning that the retarding effect of free nitrogen has less impact, possibly explaining the reduced discrepancy between the two drop temperatures.

Further reading into the effect of the hot rolling drop temperature on the rate of aluminium nitride dissolution shows why care must be taken before basing any decisions on the predicted relationships. Based on the predictions shown in Figure 6.14 one would assume that to achieve higher strain ratio values a high amount of cold reduction should be employed along with a lower drop temperature. Based on these results alone it may be tempting to continue to reduce the drop temperature in order to control the strain ratio; particularly as this reduces costs by not having to use as much energy and by allowing a lower amount of cold reduction to be employed (less energy again) to achieve similar strain ratio values as before. There are however limits to the amount that dissolution can be controlled by the drop temperature. The principle one of these is hot rolling considerations further along the mill. In order to correctly roll the steel the finishing mill temperature must be above the Ar_3 temperature (the refroidissement temperature, when the phase changes from austenite to ferrite, 910^{o}C for pure iron) so that it is still the correct phase [26, 32]. Using the model on its own may not indicate this.

6.4. Conclusions

In this chapter details of further uses of the property prediction models were discussed. The initial approach used the models to predict the effect of one process condition at a time on the final properties of continuous annealed steels. Further modifications to this work allowed the approach to consider the effect of one variable on the properties with another process condition set at different levels. The predicted relationships were compared to known relationships between process conditions and output properties to assess how well the modelling process reflected actual continuous annealing.

Through use of the single input approach it was shown that models predicting the strain ratio and strength related properties were capable of simulating some of the relationships identified by other researchers. While the general trends of the relationships were captured some of the finer details were not, with many predicted relationships exhibiting the correct shape but their scales being wrong. This discrepancy between the actual relationships and the predicted ones appeared to be greater for steels produced on CAPL; one explanation for the lower accuracy of the predictions from these models. Some of the variations between the actual relationships and predicted ones could also be attributed to the modelling approach, with historical data stored in the model possibly introducing a bias into the sensitivity analysis.

The multivariate analysis method was used to further quantify some of the relationships affecting the strain ratio of steel. Again, the predicted relationships exhibited similarities to known ones. It was shown that the predictions should be considered carefully before acting upon them as some of the predictions may represent the effects of other parameters not currently being considered. Finally, an example was highlighted showing the need to have a full grasp of the limits of the steel mill before making alterations based on any of the predictions.

CHAPTER 7 – PROJECT CONCLUSIONS

7.1. Introduction and Conclusions

The aims of the project (identified in Chapter 1) were as follows:

- Produce a model which can be used to predict the release properties of certain grades of steel produced on the continuous annealing line at Port Talbot and Llanwern.
- Produce a sensitivity tool to help identify the appropriate process window for the continuous annealing line at Port Talbot and Llanwern

The work detailed in the previous chapters has shown how a generalised regression network based model was developed based on the other modelling approaches found from the literature survey. The initial model was based on inputs selected through a combination of metallurgical understanding and correlation with the output properties. This was later adapted to include a genetic algorithm to optimise input selection. The model's predictions are based on actual process conditions negating the need for any additional data gathering exercises such as determining grain size. In addition, a sensitivity analysis method was developed based on the fully trained models. This approach can be used to determine the effect of single inputs or to analyse the compound effect of two varying inputs. This approach was used to help validate the models and find areas of weakness by comparing the predicted relationships with known metallurgical principles.

This work has provided several conclusions regarding the prediction of mechanical properties based on processing conditions of continuous annealed steels. A summary of these findings is detailed below.

- Using multiple linear regression analysis proved to be an ineffective way of modelling the properties of continuous annealed steels. The linear approximations were not powerful enough to fully describe the annealing process. The accuracy of such models was highest using data which had met specification. Attempting to reduce the complexity of the model by using fewer inputs resulted in the accuracy of the models decreasing.
- Using a generalised regression network in place of the multiple linear regression approach yielded a significant improvement in the predictive accuracy for the majority of the properties under investigation. Although the mean square error was low the accuracy of the elongation model was found to still be poor. Reducing the number of inputs based on their correlation with the output property resulted in a slightly higher error than using all available inputs, however this approach was still better than basic regression.
- The use of a genetic algorithm to optimise input selection along with a constant spread value was found to further increase the predictive accuracy of the models. Such an approach yielded higher accuracies than had previously been obtained.
- Optimising the spread value for each new set of input conditions was found to have a limited effect on the predictive accuracy of models trained in this way. The time taken to train models using this method was significantly greater than any previous training routine. For this reason the constant spread method was carried forward.
- Inputs chose by this training routine mirror those factors that have been shown by other researchers to affect the properties of steel. This suggests that the developed models may be a suitable method to assess these relationships and possibly quantify them.
- These findings suggest that generalised regression network based models combined with a genetic algorithm are a suitable non-linear method for predicting many of the properties of annealed steels for all the grades under consideration.
- By introducing specially designed input sets to the fully trained model predictions could be made about the relationships that exist between process conditions and final

mechanical properties. Through the use of this it was shown that models predicting the strain ratio and strength related properties were capable of simulating some of the relationships identified by other researchers. While the general trends of the relationships were captured some of the finer details were not, with many predicted relationships exhibiting the correct shape but their scales being wrong.

- This discrepancy between the actual relationships and the predicted ones appeared to be greater for models of steels produced on CAPL. This offered some insight into the lower accuracy of the predictions from these models.
- Some of the variations between the actual relationships and predicted ones could also be attributed to the modelling approach, with historical data stored in the model possibly introducing a bias into the sensitivity analysis.
- The same technique was used for multivariate analysis. This was shown using further analysis of some of the relationships affecting the strain ratio of steel. Again, the predicted relationships exhibited similarities to known ones.
- It was shown that the predictions should be considered carefully before acting upon them as some of the predictions may represent the effects of other parameters not currently being considered. An example was highlighted showing the need to have a full grasp of the limits of the steel mill before making alterations based on any of the predictions.

7.2. Recommendations and Further Work

The generalised regressions based models put forward in this work require constant monitoring and modification if they are to meet their full potential. One of the benefits of such a model is that it can help reduce the amount of tensile testing that needs to be carried out. In order for this to happen the model will need to be compared to the relevant standards (when available). It is suggested that a trial period should be initiated, where the model is run in conjunction with tensile tests so that any problems in fully implementing the model can be assessed. The model would predict the properties of the steel and a judgement of the suitability of the prediction can be made, based on the recorded predictive error, standard deviation etc.

One key area that still needs to be considered is how the models will be maintained. This means that complete elimination of tensile testing would not be possible, as data will be needed to retrain the model. Choosing when to retrain the model and what data to use should be investigated. The simple approach of slowly gathering data and then retraining a new model may provide an accurate prediction model which takes into account any process drift (caused by plant overhauls, improvements, new equipment, different operators, etc) however it may not be suitable for use with the sensitivity analysis methodology. The sensitivity model requires a broad spread of data for it to work correctly. There may be historic cases with specific process conditions, such as extremely high or low values, which may be useful for making predictions. Using new data to make a model would discard these. The best approach may be to develop two distinct models; one to be used as an online prediction tool and the other used as the basis of the sensitivity analysis model. For example, physical testing could be cut down to one in three coils with the predictive tool being retrained on a regular basis using new data. The sensitivity tool could be retrained less frequently, with data selected using some form of ranking system. Coils processed with specific processing conditions would be given a higher ranking than common ones. This adoption of this kind of approach would allow both models to function well and mitigate any negative effects that the different data sets would have on each model.

As with many engineering problems the methodology presented is not likely to be the only way of predicting the properties of annealed steels. Whilst an artificial neural network approach was initially tried, and then rejected, as a possible route that this project would take; only a limited topography and training routine were used. Many different forms of neural networks exist and likewise many different training regimes. Further investigation into any number of these approaches may yield similar results to those put forward here. There is also the possibility of looking at entirely different research fields to obtain a solution.

Examples of finite element and head transfer methods being used to model batch annealing of coils were found [63]. Though likely to be more complicated it is not difficult to envisage such an approach being applied to the continuous annealing process. A basic approach may see these methodologies being used to determine the temperature profiles of different segments of the strip as it passes through the various processes. These results could then be used in conjunction with the model developed in this work, or one similar, to give predictions of the through coil properties. A more complex approach could bring together the research into recrystallization mechanisms and produce a computation model of that process. The relationships between grain size and texture on mechanical properties could then be used to produce predictions.

The model developed in this thesis was developed as a 'non-adding' process, in that no additional measurement devices or sensors were to be added to the process to aid the prediction. The use of additional measurement equipment, such as cameras, x-ray or magnetism, could be used to produce the predictions alone or as additional information for other models. Some examples of these approaches already exist [60].

Future technology will also allow the model to be further developed and its efficiency increased. Though it is not possible to second guess all these developments some trends can easily be extrapolated, for example the development of computing. With increased computing power constantly becoming more affordable it may not be long before the genetic algorithm section of this work may become superfluous, as the time taken to test the whole solution set will have diminished.

The robustness of the generalised regression approach was shown many times throughout this work. The initial model was developed to predict the properties of one grade of steel produced by a specific processing route. The final modelling approach was capable of being used for several grades of steel made on different processing lines. Very little modification was required to achieve this. This suggests that this modelling approach could be used to predict the properties of further grades of continuous annealed steel and applied to different processing lines. As continuous annealing is one of the final process applied to strip steel and the model relies on inputs from the whole steel making process it may well be possible to use a modified version to predict the properties of steel as different processing stages (it would be interesting to compare the results of such a model with others available in the literature predicting the properties of hot rolled steels). It may also be possible to utilise the same modelling approach to model other large scale industrial applications with several processing steps. The modelling approach may be used as a predictive tool for a variety of fields; ranging from predicting the likelihood of a failure in a part based on its specifications and use to areas such as medical engineering, where the properties of tissues may be investigated.

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APPENDIX I – INITIAL NEURAL NETWORK APPROACH

i.i Introduction

Neural network approaches have been shown to have significant potential during the development of prediction models [A-C]. In order to make full use of this potential the design, or architecture, of the network needs to be suitably optimised prior to its implementation. With a multiple regression type approach understanding the architecture of the model and optimising it prior to use is relatively simple, with neural networks this is not the case. For these reasons the following factors need to be carefully considered; the type of network used, the number of neurons in the hidden layer, what transfer functions should be used and what training algorithms will be employed.

Findings during the initial literature review for this project suggest that feedforward multilayer preceptron networks are most suitable for pattern recognition and prediction situations. For this reason a network was designed with one hidden layer. As a starting point, the number of neurons in this layer was based on the Hecht-Kolomogorov theorem (cited in[D]). This states that the number of neurons in the hidden layer is equal to twice the number of inputs plus one. This value would be altered should it be deemed necessary.

The neurons in the hidden layer utilised the tansigmoid function, which gives rise to their outputs varying between -1 and 1, as shown in Figure i.1.

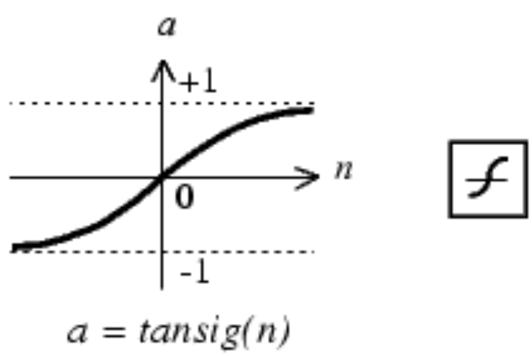

Figure i.1: Illustration of tansigmoid function

The output neurons utilised a linear function. This allowed for the final output to be scaled to any value based on the output from the tansigmoid layer. The complete network can be seen in Figure i.2, as shown by Matlab.

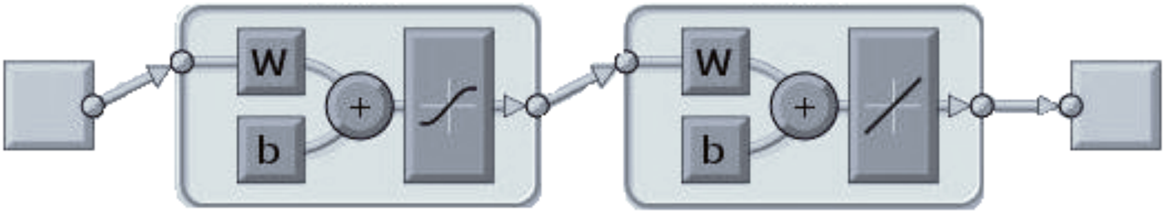

Figure i.2: Initial network design

The final choice in the design of the network was how to train the network. This decision was twofold; firstly whether to use a supervised or unsupervised training regime and secondly how the data should be presented to the network.

Supervised learning adjusts the weights of neurons based on the difference between the network outputs and the desired actual outputs. This method requires that a supervisor, or teacher, is needed to provide the desired outputs. Unsupervised learning does not require the desired outputs to be known. A network trained in this way only requires input parameters to be presented to it. Weights are then adjusted to cluster the input patterns into groups which have similar features. A supervised training regime was employed, due to the vast quantity of data available and therefore the known outputs.

The initial model was programmed using raw data, with the only pre-processing being the removal of incomplete coil data and the removal of unnecessary columns. The network was trained using the Lavenberg-Marquardt algorithm, as other research had highlighted this to be the most suitable to this type of situation [E]. Matlab randomly sorted the data into three training sets; training data, validation data and test data. In simple terms the different sets act in the following ways:

Training Data: This data is used to shape the network. The data is passed through the network and the output error calculated. The network weights are then altered accordingly.

Validation Data: This data is used to measure the networks generalisation. When the generalisation stops improving, for a given number of training interval (epochs), the training of the network in halted.

Test Data: This data has no effect on training and so provides an independent measure of the network's performance during and after training.

The data was divided so that the training data set contained 70% of the overall data, with the rest being split evenly between the other two sets.

The modelling progress could be followed using a value which Matlab calls 'Performance'. Closer inspection revealed this to be the mean square error (MSE) of the predicted values, in particular that of the validation data set. Once this value reached a minimum Matlab would then continue train the network for a set amount of epochs (the default value was six) to see if any further reduction occurred. When no reduction occurred in the allotted time training stopped. Once training was completed Matlab could then produce regression plots for all three data sets as well as one for all the available data. This plot could also be produced in real time, though was found to slow down the training process. Further plots could be produced showing the how the performance value for each data set varied with training intervals and the training state of the network.

i.ii Initial Results and Problems

This section contains details of work that was carried out before the investigation into data cleaning. Although the results of this work are therefore going to be somewhat insignificant it was felt that details of the methods used and some of the findings were worth documenting.

The first approach to modelling using neural networks was to try and model all the properties using one neural network, with an output representing each one. This was carried out on the

DC05/06 data set. The network made use of the 40 inputs listed in Chapter 3, and so had a hidden layer with 81 neurons. The first attempt to do this used data that had not been normalised. The results obtained from this model are shown in Figure i.3.

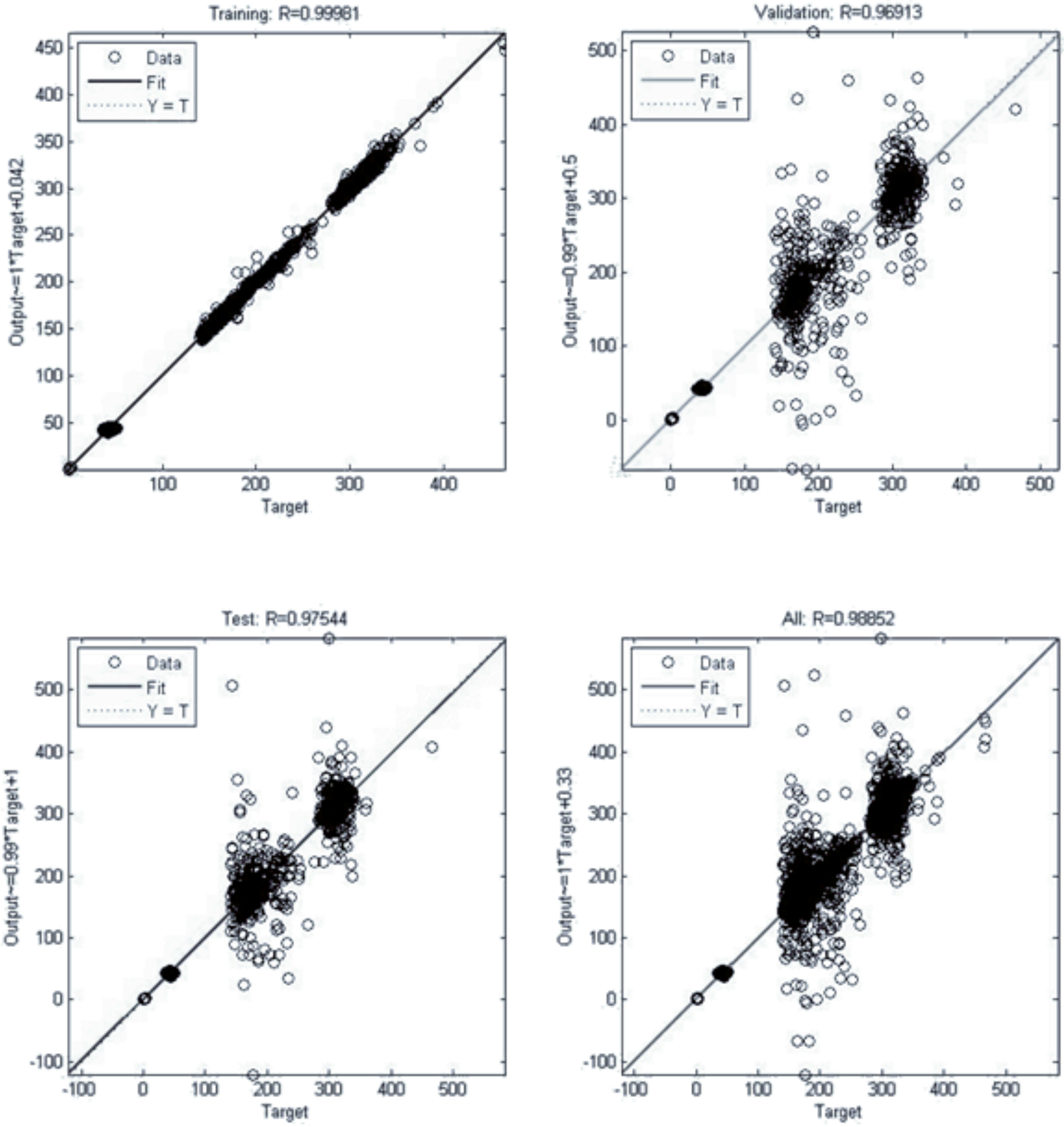

Figure i.3: Results from neural network modelling all properties of DC05/06 steels, no normalisation

The training set reflects the actual result very closely, as is common in most of the test carried out. There is a large spread however when looking at the validation and test data sets. This is particularly apparent for the ultimate tensile strength and proof stress values (the two groups with greater magnitude). It is difficult to tell the accuracy of the prediction for strain hardening, elongation and anisotropy due to the scale of the charts.

These results were initially seen as encouraging, based purely on the statistical data that could be obtained from them, such as correlation. It was only upon closer inspection that it was realised that high values for such data was obtained due to the differing magnitudes of the properties. This highlighted the need for the properties to be normalised. All data, both inputs and outputs, was normalised and a new network setup. The results obtained from this network are shown in Figure i.4.

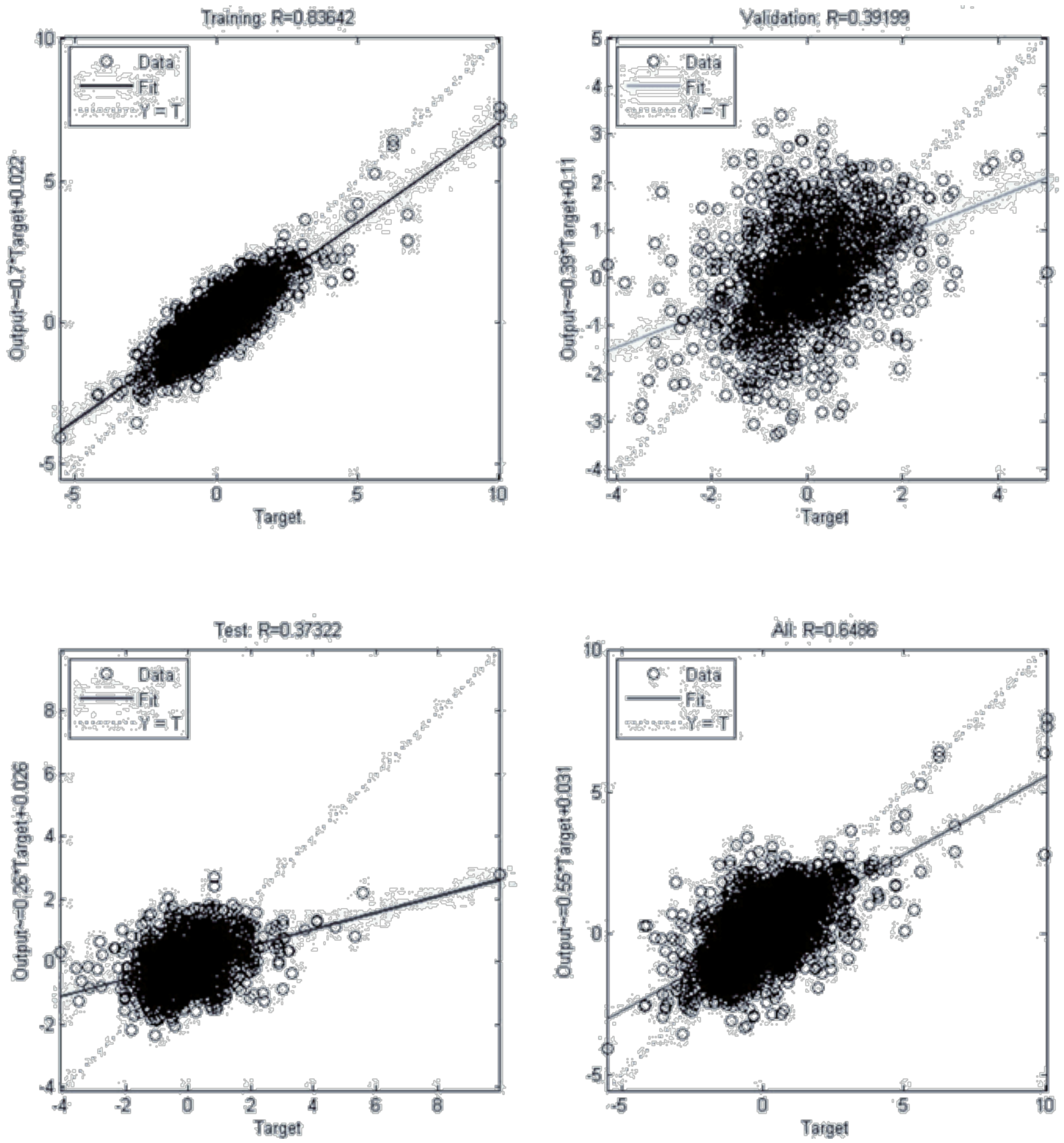

Figure i.4: Results from neural network modelling all properties of DC05/06 steels, all data normalised

As can be seen from the above figure the results obtained from this model were poor. Again the model was able to make good predictions on the training data, as would be expected. The results for the validation and test data sets did not match this accuracy. With this approach, the predictive accuracy for individual properties could not be obtained from the chart alone. The failures of this model are likely to be due to the complexity of the data. For this reason it was decided to produce individual models for each of the properties, as well as reducing the number of model inputs, in an attempt to try and simplify the problem.

i.iii Improved Neural Network Results

In order to reduce the number of inputs to the network an m-file was written to only select those that had a statistical significance on the output properties. This selection was based on correlation coefficients between the input variables and the output properties: only those with an absolute value greater than 0.1 were included.

The first model made use of all available data for the DC05 and DC06 grade steels. For the purpose of this work only the results for ultimate tensile strength are shown. For this model this value is not normalised. After removing the split coils from the data 2456 coils remained. The input selection m-file was used, with ten inputs being chosen. These were: gauge, radiant tube furnace temperature, soak temperature, high gas jet cooling temperature, reheat overage temperature, soak time, furnace tension, temper mill exit tension, temper mill load and temper mill speed. The results of training this model are shown in Figure i.5.

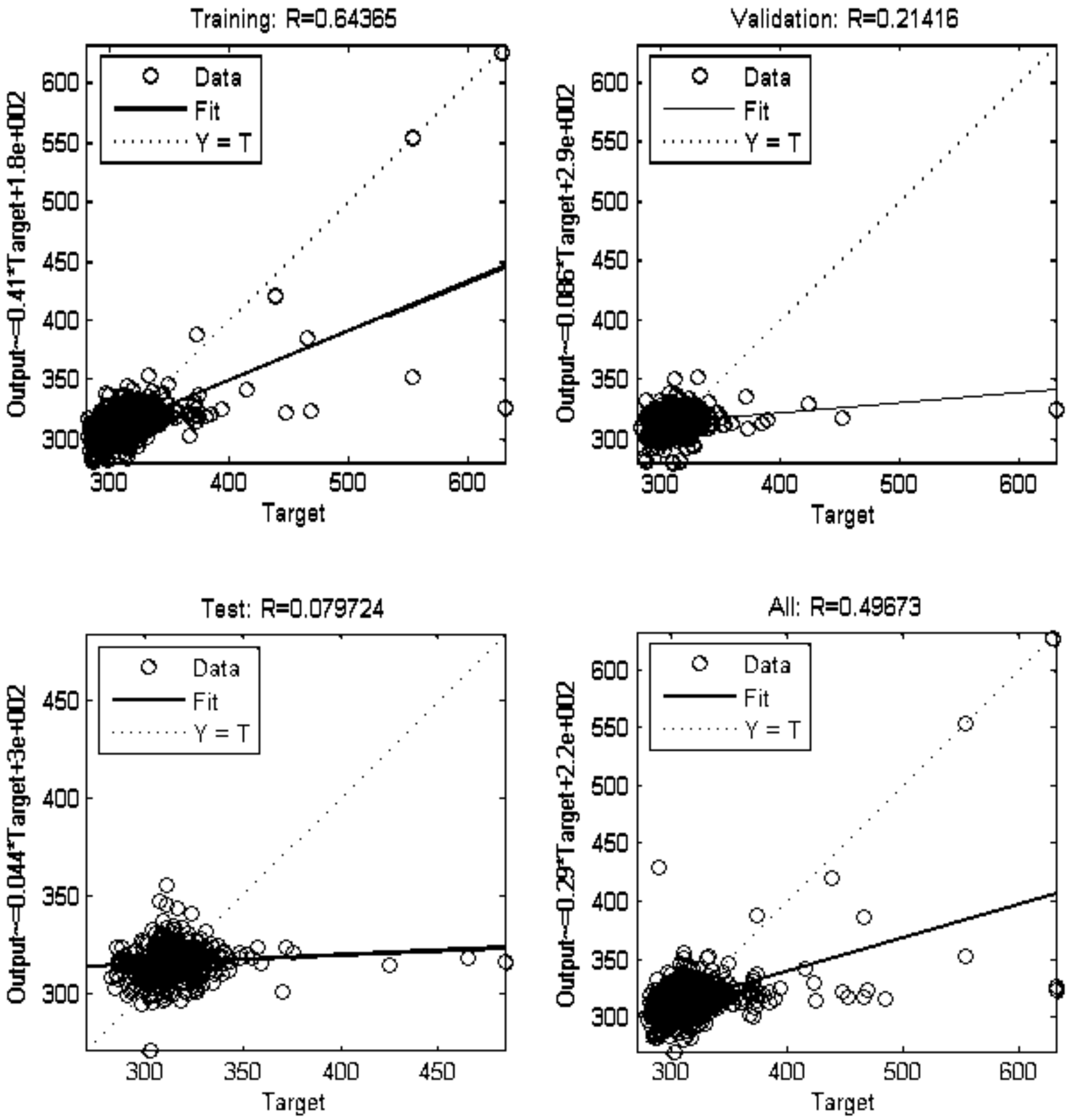

Figure i.5: Results from neural network modelling ultimate tensile strength of DC05/06 steels, input data normalised

The model failed to accurately predict the training data. Closer inspection of the results indicates that the higher ultimate tensile strength values, above the specified maximum value, were particularly difficult to model. A likely cause for this problem maybe that there are so few data points around this area for the model to learn from. In order to assess the capabilities of this approach a new model was trained that excluded the failed data points.

Sixty-nine coils were removed for failing to meet the ultimate tensile strength specification, leaving 2387 coils. The same m-file was used to select the inputs, with it fifteen inputs being chosen. These were: gauge, weight, radiant tube furnace temperature, soak temperature, high gas jet cooling temperature, reheat overage temperature, high gas jet cooling rate, soak time, furnace tension, temper mill tension in, temper mill exit tension, temper mill load, temper mill speed, cold reduction, and phosphorus. The results for this model are shown in Figure i.6.

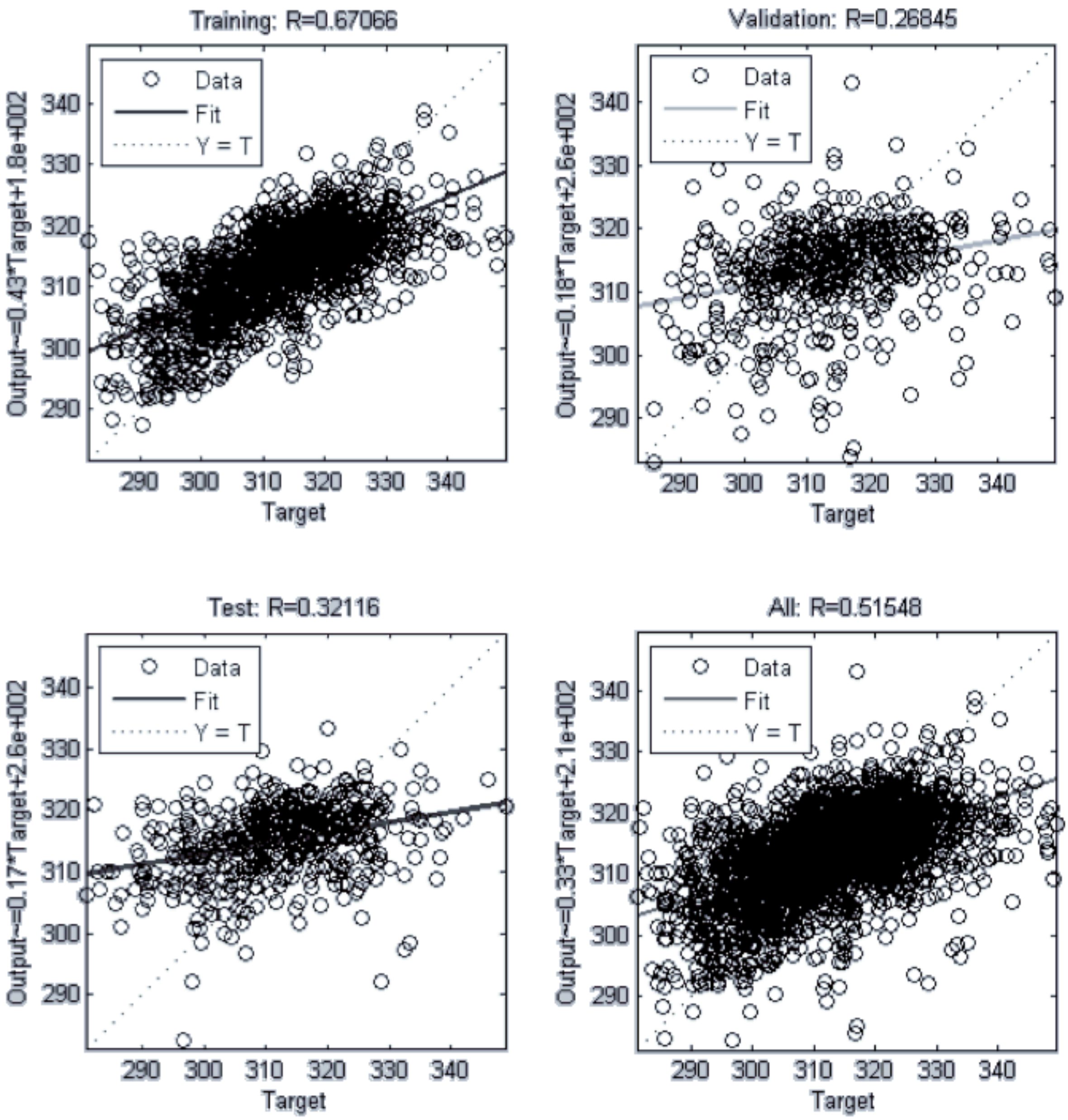

Figure i.6: Results from neural network modelling ultimate tensile strength of DC05/06 steels, input data normalised with no failed coils

An initial view of these results, based on the training data, may lead to the conclusion that these results are no better than results obtained from other models. Inspection of the test data results, the unseen data not used to train the model, shows some improvements of this model over the previous one. The results are still not as accurate as one would hope for, with large discrepancies between many of the predicted and actual ultimate tensile strength values. The poor results achieved, based on training data, are another indication of the failings of this modelling attempt.

The approach detailed in this section failed to produce accurate results. This outcome was disappointing when compared to results obtained by other researchers using the same methods. The results shown here represent the best achieved from several models produced using different inputs and network configurations. Most importantly, a considerable amount of time was spent on this approach with seemingly very little achieved. For this reason it was decided to try and find a different predictive method that could be used.

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