10. Conclusions and Future Work

The aim of the project was to create neural network models to characterise the mechanical properties of austenitic stainless steels. From this work, a genetic algorithm program was created, and later used, to find a host of compositions that lead to the same yield or ultimate tensile strength.

Research commenced with a review of the literature. Basic principles of austenitic stainless steel were outlined, including everyday uses. It was also shown that there are many factors that affect steel strength. Mechanisms to compensate for imperfections and further enhance mechanical properties were described. However, there are advantages and disadvantages with each approach, which somewhat complicates the situation.

Simple linear regression models for steel strength have been developed in the past and are used in industry with relative success. However, it is likely that these models do not take into account the non-linearity of the problem, neither prediction uncertainties. To improve upon this, neural network models were developed for yield strength and UTS as a function of composition, temperature and heat treatment temperature.

Both of these models were tested with various compositions to investigate how the different inputs influenced mechanical behaviour. Analysis through predictions and contour plots showed good agreement with the literature. Hence the models were considered to be a good reflection of both yield strength and UTS.

However, the models are limited in applicability. There is always a need for more data to supplement their knowledge and improve predictability. Furthermore, there are 19 variables, so extra inputs such as heat treatment time and the dimensions of tested steel could be included. Nevertheless, extrapolation confidence is always gauged by the magnitude of uncertainty, as shown by the error bars.

A genetic algorithm (GA) program was also developed and used for this project, to expand the use of the neural network. GAs allow the efficient search of input space, given a fitting function. Definitions and concepts were explained, including the different parameters, which guide the optimisation process.

To commence optimisation, a random number generator applied values to all genes in different chromosomes. They were then put through the neural network model committee, and ranked according to a fitness function. All chromosomes were subsequently affected by different parameters, such as mutation and crossover. The aim was to achieve a specified output value.

It was first determined that the GA process was better than a random search. As search efficiency is important, different parameters were varied to investigate their effects on convergence speed. Enlarging generations, populations and crossover rates increased the amount of data shared amongst populations and the chances of convergence upon a given target.

Optimal parameters were finally applied to find a target outside the database. This procedure had limited success, but reasonable compositional values were still found for yield strengths of approximately 400 MPa.

However, time was found to be the main limiting factor, as searches could have continued over longer periods. Hence further work could include searches over a wider input space for multiple compositions over many thousands of generations. In addition, now that a universal search algorithm has been developed, this technique can be applied for many other applications where a neural network exists.