Chapter 8

Summary and Suggestions for Further Work

The complexity of welding alloys has in the past prevented the development of generalised models capable of giving quantitative estimates of anything other than the most simple mechanical properties. It has been possible, using a neural network technique within a Bayesian framework, to develop a set of models dealing with the yield strength, ultimate tensile strength, ductility and impact toughness of weld metals as a function of the chemical composition and heat treatment. The models are based on a vast quantity of published experimental data which were all digitised and assessed for model development.

Neural networks are used in circumstances where the complexity is difficult to deal with using scientific principles. For this same reason, the trained networks cannot ever be fully tested since it is hard to imagine how multi–fold interactions between the inputs can affect the outcome. Nevertheless, an attempt was made to assess whether the networks reproduced the known physical metallurgy. For example, the effect of carbon and manganese on the yield strength of low–alloy weld deposits. In almost all cases considered, the networks could be shown to recognise known trends, taking into account the error estimates.

However, in some cases, such as when considering the effect of tungsten on the strength of low–alloy steel welds, it was evident that the models lacked knowledge to such an extent as to make the predictions unphysical. The situation was corrected by adapting steel data to represent welds, and the resulting model was demonstrated to behave properly. This example illustrates that the networks should not be used blindly but rather as an aid to design.

The combined set of models, together with experience from physical metallurgy, were then used to propose a new tungsten–containing welding alloy which can be used in circumstances where post–weld heat treatments are not practical. This proved to be successful at the first attempt; subsequently, the models have been used successfully by others in a similar way, to invent welding alloys without doing experiments.

The tempering resistance of the tungsten–containing weld has been studied experimentally and compared with that of a number of alloys. This work indicates that the replacement of molybdenum by tungsten in creep–resistant alloys leads to a lower as–deposited hardness which can be exploited to eliminate post–weld heat treatments. The creep strength can nevertheless (probably) be maintained by the use of vanadium.

The models developed here contain the chemical composition, welding heat input and heat treatment as inputs. These inputs effectively contain information about the microstructure. However, it would be useful to include microstructure directly. There are insufficient experimental data available to create a large enough dataset for analysis. Nevertheless, there are now physical models which can provide estimates of microstructure, at least for the so–called carbon–manganese alloys. In future work it would be useful to include *calculated* microstructural parameters, as well as chemical composition *etc.* as inputs in the neural network models in order to find relationships which are more physically meaningful.

Future work could focus on the development of a quantitative tempering theory since it is not yet possible to predict, using physical models, the tensile properties as a function of heat treatment following the deposition of the weld. This really is surprising given the enormous amount of published research on welds.