Comparative study of cold-formed steel members by using neural networks

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Cold-formed steel members have a wide range of possible cross-sectional profiles, aspect ratios and sizes. While this flexibility gives the designer almost unlimited freedom in shaping the members, it makes the selection of the most economical design for a particular application quite difficult. The situation is further aggravated by the complex rules that govern cold-formed member design and the combined liability of cold-formed members to different failure modes. This paper investigates the potential for using artificial neural networks to overcome these design problems, with emphasis on the most commonly used channel and Z members. Artificial neural networks are trained using data relating the members' cross-sectional profile and size to the load carrying capacity. The networks are then developed into reliable design tools able to select the best cross-sectional dimensions for any given load.

تتواجد القطاعات المعدنية المشكلة على البارد بأشكال وإبعاد عديدة وبينما تعطى هذه الأشكال الكثيرة حرية كبيرة للمصمم لأختيار القطاع الملائم من حيث الشكل. فإن اختيار أنسب القطاعات اقتصاديا من بين هذه المجموعة الكبيرة من الأشكال صعب جدا. هذه الصعوبة تأتى من صعوبة المعادلات الخاصة بالتصميم لمثل هذه النوعية من القطاعات نظرا لقابلية هذه القطاعات للانهيار بواسطة أكثر من نوع من أنواع الأنبعاج نظرا لصغر سمك هذه القطاعات.فى هذا البحث يتم دراسة مدى أمكانية استخدام الشبكات العصبية الاصطناعية للتغلب على مشكلات التصميم لمثل هذه القطاعات ويتم المقارنه بين أكثر الأشكال شيوعا وهى القطاعات على شكل (*C*) و شكل (*Z*). يتم فى هذا البحث تدريب الشبكات العصبية المستخدمة بواسطة بيانات تغطى أكبر قدر من الأحمال العمودية التى يمكن أن يتحملها أى عضو ضغط. بعد تدريب الشبكات العصبية تم اختبارها وقد أعطيت قيم جيده جدا بنسب خطأ بسيطة جدا.

Keywords: Neural networks, Cold-formed steel, Design, Structural applications

1. Introduction

Cold-formed steel members are finding increasing acceptance in the construction markets as primary and secondary structural elements. The reasons behind their increasing popularity include:

- High strength:weight and stiffness:weight ratios compared with hot-rolled steel allowing better use of material and easier transportation, handling, and erection;
- Ease of fabrication that allows fast and large-volume production.

These advantages can result in more cost-effective designs, when compared with hot-rolled steel, especially in short-span applications [1,2].

Cold-Formed (CF) members can be produced in a wide variety of section profiles, the most commonly used of which are the channels and the Z sections shown in fig. 1. The basic shapes can be enhanced with flange stiffeners to improve the members' resistance to both local and overall buckling [3]. The members can also be manufactured with a wide range of aspect ratios, sizes and wall thicknesses, with direct impact on the members' efficiency.

While this freedom to modify the cross-section of CF members provides a desirable flexibility to the structural designer, it makes arriving at the optimum design for a given application a difficult and lengthy process.

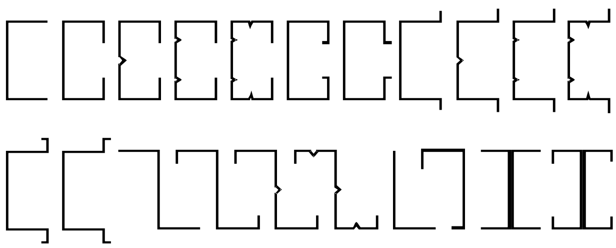


Fig. 1. Some of the cold-formed sections commonly used in construction applications.

The problem is compounded by the complex nature of the analysis procedure - mainly because of the combined liability to both local and overall failure buckling modes [4,5].

The project described in this paper seeks to overcome this problem by developing a new design methodology for CF members, which can:

- Provide the most efficient cross-section, chosen from a wide range of profiles, aspect ratios and sizes;
- Allow for varying design criteria, e.g. in one situation, least weight and cost may be the main concerns, whereas in another, member connectivity could be paramount;
- Consider all possible failure modes;
- Satisfy current design codes;
- Enable designers to be in full control.

The project carried out between Arab Academy and University of Dundee, UK, uses Neural Network (NN) technology to create a set of design tools capable of selecting the best cross-sectional profile and size for any given loading condition. This paper focuses only on the design with plain and lipped channel and Z sections under concentric compression as an example of the current work. After a brief introduction to neural networks and their features, the construction and assessment of the NN design tools are explained in detail. Focus has been given to finding the network architecture that could yield the best accuracy and reliability, as this should be of much value in future work involving use of NN tools.

2. What are Neural Networks?

Neural Networks (NNs) are artificial intelligence algorithms for cognitive tasks, such as learning and optimisation. They have four chief advantages over other artificial intelligence methods. They can (a) learn from examples and previous knowledge, (b) encapsulate a great deal of knowledge in a very efficient manner, (c) deal with complex design problems where it is almost impossible to formulate the governing rules in the form of a traditional mathematical model and (d) take account of factors that are not easily quantifiable. In cold-formed member design, they could utilise information effectively on the vast range of possible profiles and aspect ratios, and consider both quantitative factors (e.g. strength and weight) and qualitative factors (e.g. connectivity and availability).

A neural network commonly consists of a number of interconnected processing units (called nodes), arranged in at least three layers [6-8]:

- An input layer that receives input values;
- An output layer that reports the final answers; and
- One or more hidden layers between the input and output layers as shown in fig. 2.

The hidden layers extract useful features from the input data and use them to predict the values of the output nodes. Fig. 2 shows that each node in a hidden layer is connected to all the nodes in the two adjacent layers using "weighted" links. The weight of each link is used as a measure of the importance of this particular link to the optimisation problem, which the network is trying to solve.

Before using the network, it should be adequately trained using a large set of solved examples (i.e. given input and output values) that covers all possible problem areas. The network uses these examples to adjust the weights of its inter-node links such that the error in the output is minimised. In this process, the weights of all links feeding into the same node are combined, usually by summation, and the resulting value is modified using a non-linear transfer function before it is passed to the output path of the node [9-11]. The most common transfer functions are the hyperbolic tangent (tanh) and the sigmoid functions.

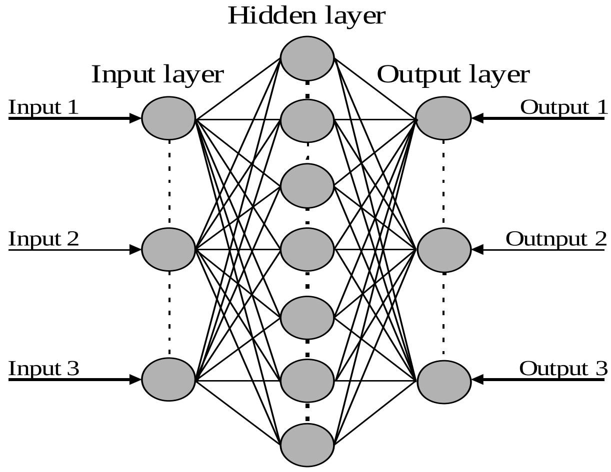


Fig. 2. Neurel network with one hidden layer.

A technique called back-propagation is used in this work to train the adopted feed-forward networks [12]. In this technique, the error found in the output layer is propagated back through the network to the input layer, and this process of calculating the error and propagating it back is repeated until the error is reduced to a specific low value. Once this has been achieved, training is considered to be complete and the inter-node link weights are registered and kept unchanged as shown in the flow chart in fig. 3. Then once the network has been tested successfully on further data, it is considered ready to respond to new input data and predict the corresponding output. In this stage of operation, the network is usually extremely easy and fast to use.

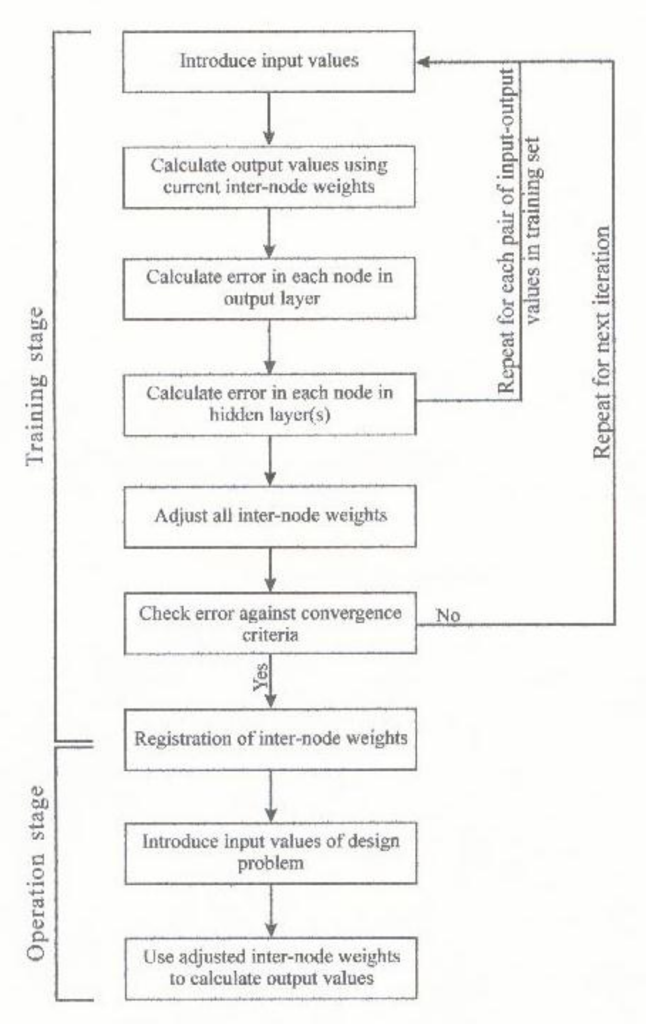


Fig. 3. Flow chart for the neural network training and operation stages.

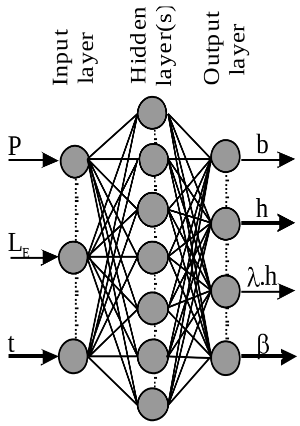


Fig. 4. Neural network to choose the best section profile and dimensions (β = 1 for channel sections and β = 2 for *Z* sections).

3. Using neural networks in CF member design

In total, six neural networks have been developed in this work to design CF steel members with plain and lipped channel and Z sections under axial compression. The constructions of the networks are depicted in figs. 4 and 5. Earlier work on NN applications in structural engineering has helped guide the work presented in this paper [13-20]. The work by Adeli and Karim [20], which lays the mathematical foundation for the automated optimum design of cold-formed steel members, is particularly important.

4. Training of neural networks

In order to train the networks over the practical range of possible design problems, a large database of training examples was formed. The database covered wide variations of the following important parameters to include the great majority of design problems the network would be expected to handle:

- Depth of section, h = 200, 205, 210... 700 mm, see fig. 6;
- Wall thickness, t = 2, 3, 4 mm;
- Ratio of lip depth to total depth, λ = 0.0, 0.1, 0.2, and 0.3;
- Effective buckling length of section, L_E = 2000, 3000,..., 7000mm;
- Section aspect ratio, b/h = 0.3, 0.4,...,0.7; and

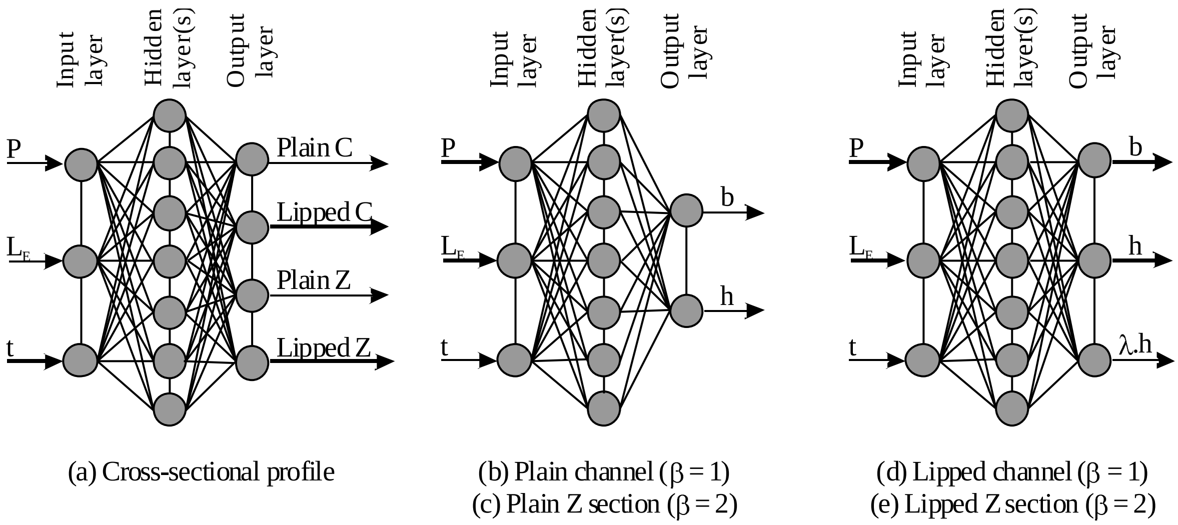


Fig. 5. Neural network to predict the cross-sectional profile followed by four networks to choose the best section dimensions.

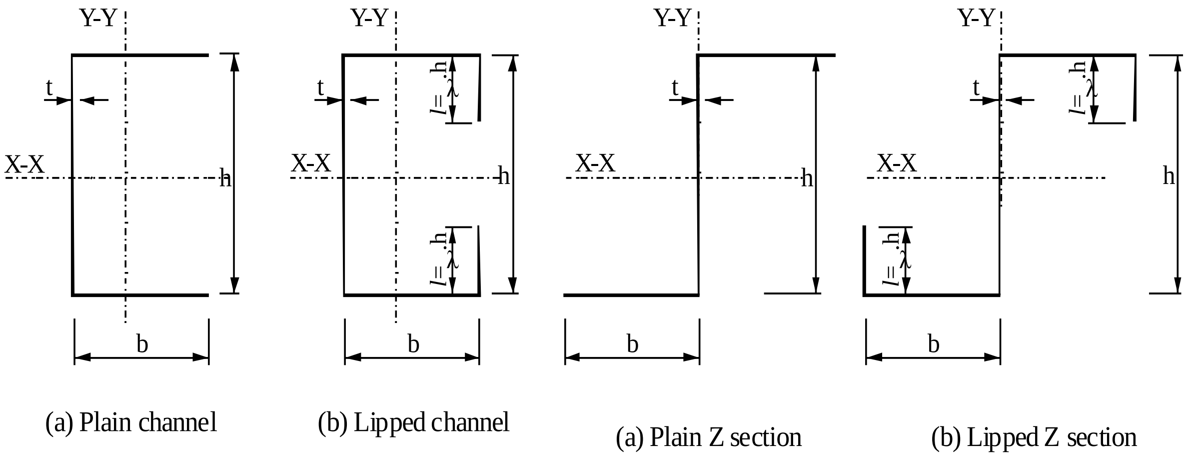


Fig. 6. Cross-sectional dimensions.

• Factor β to distinguish between channel and Z sections, β = 1 for channel sections and 2 for Z sections.

In all cases, the material yield strength, Y_s, was taken as 280 N/mm^2. All members were subjected only to axial compression forces. They would therefore be liable to the effects of local buckling and to failure by either flexural or torsional flexural buckling.

The design loads for the members included in the database were calculated in accordance with BS5950, Part 5 [21]. The calculations depicted in the flow chart in fig. 7, were coded in a Visual Basic program so that all members could be analysed simultaneously. The program was also designed to select from this large number of members the "best" members, which were considered most suitable for inclusion in the training set, see fig. 8. The definition of the "best" members was based on a single efficiency criterion – either the strength: weight ratio ($\frac{P_d}{[h+2b+2h\lambda]\cdot t\;\rho}$, where ρ is the material density), or the strength: cost ratio. In the latter case, consideration is given to both the material content of the member as well as the number of folds in the section.

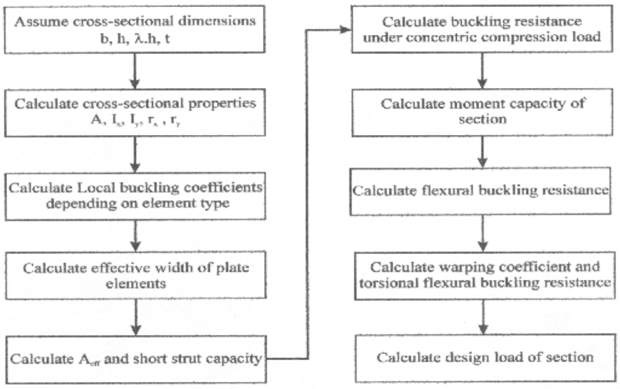


Fig. 7. Flow chart for the steps of analysis of cold-formed members under compression.

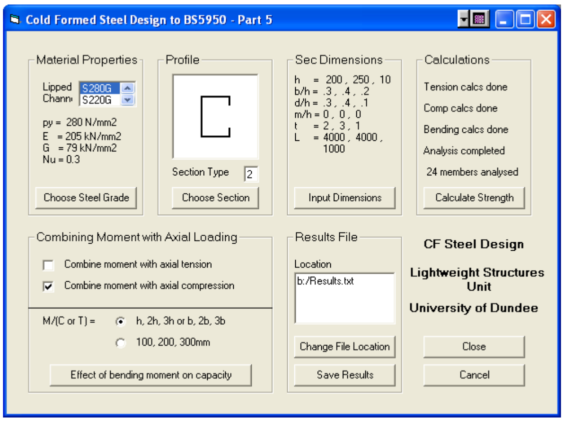


Fig. 8. Visual basic program for CF member analysis to BS5950-part 5.

In selecting the best designs, the members analysed were divided into small groups according to their load carrying capacities, and from every group, the member with the highest efficiency was selected for inclusion in the training set. The size of each group, from which the section with the highest efficiency was selected, was set such that the increment in load capacity between groups was 10kN, based on earlier work by Elkassas et al. [22,23]. The size of the training sets resulting from the selection process and the range of strength covered in each case are given in table 1.

5. Stages of development

The objective of the research was to develop reliable design tools capable of choosing the optimum section *profile* and *dimensions* for a given load. In achieving this objective, two strategies were trialled:

- In the first strategy, one large network was built and trained using combined data related to the four profiles considered, see fig. 4. The network was trained to choose the optimum *profile* and cross-sectional *dimensions* that would satisfy the given load.
- In the second strategy, one network was built to choose the cross-sectional *profile* that was mostly likely able to produce the best performance. This was followed by four separate networks, each trained to choose the optimum cross-sectional *dimensions* if a particular profile was chosen by the first network, see figs. 5 and 9. An advantage of this strategy is that it gives the designer more control to use his own judgement by allowing him to over-rule the choice of the first network and select a different profile.

In all cases, the networks were built and trained using the Neural Connection software known for its reliability and wide use [24].

6. Parametric study

The neural networks constructed in this work were subjected to a lengthy parametric study in the search for the architecture that could yield the best possible accuracy at least cost. The study covered the following parameters:

- The number of hidden layers: either one or two;
- The number of nodes in each hidden layer: between 3 and 21; and
- The transfer function: either a tanh function or a sigmoid function.

Note that in some cases, particularly for plain sections, it was not possible to increase the number of nodes in the hidden layers to 21. This was because in these cases, the number of weights in the system would have exceeded the number of outputs × the number of records in the training set, resulting in the overfitting problem in the neural network. This problem is described in detail in refs. [6-8].

Changing the above parameters offered the opportunity to operate the neural networks with different architectures. By assessing the accuracy in each case and examining the significant trends in the network's reliability,

Table 1
Size and strength range in training datasets

Profile	Number of members nalysed	Number of members selected for inclusion set	Strength	
			From	To
Plain channel	9.090	93	12.7	225.4
Lipped channel	27.270	393	17.2	690.3
Plain Z	9.090	159	11.1	402.0
Lipped Z	27.270	251	26.2	767.3
All four profiles	72.720	467	11.1	767.3

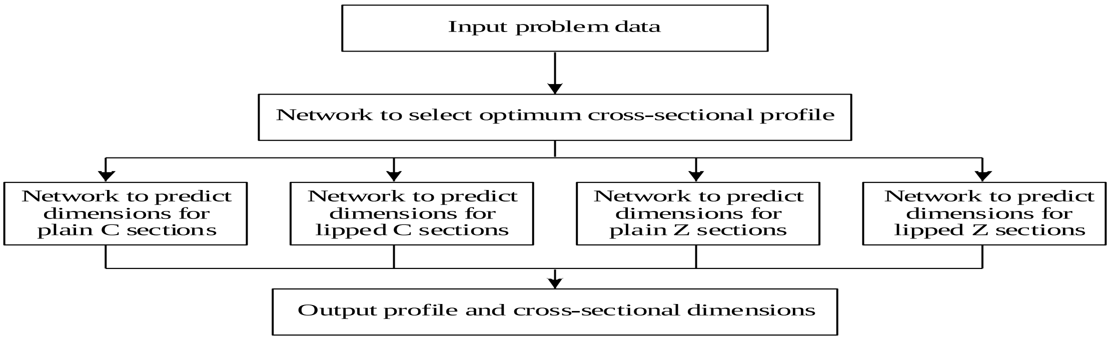


Fig. 9. Flow chart for the steps to choose a profile and predict the cross-sectional dimensions.

the neural network architecture most able to arrive at the optimum design could be identified. The results of this work are presented in the following sections of the paper.

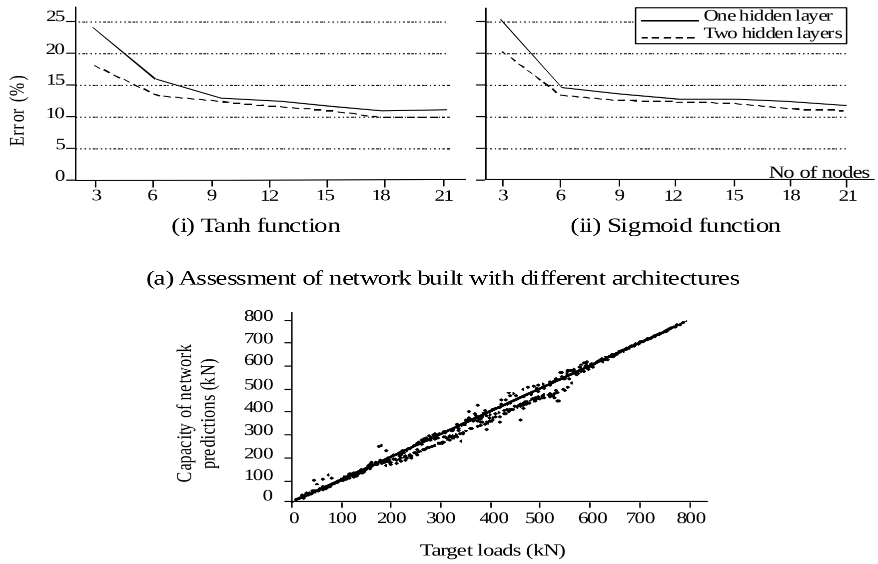
7. Assessment of design neural network-first strategy

In the first part of this work, a large network was built and trained using combined data related to plain and lipped channel and Z sections. The network was trained to choose the optimum cross-sectional profile and dimensions that satisfy a given compression load. The accuracy of the network over a wide range of strength (P_d) values and while using different numbers of hidden layers and hidden nodes and different transfer functions is depicted in fig. 10. The errors presented in the figure are the mean of the absolute errors of the neural network' failure load predictions against the failure loads predicted by BS5950: Part 5 (21). Overall, it is evident that the error levels of the network designs were high, above 10% in all cases. This certainly casts a shadow on the reliability of this strategy, which employs a large network trained with a large set of training data. The discussion, however, continues below to see how the accuracy was affected by changing the network architecture.

The results in fig. 10 show a gradual improvement in accuracy (smaller errors) with more hidden nodes. Initially, the effect was significant with 35% average improvement in accuracy associated with using 6 hidden nodes instead of 3. Increasing the number of nodes further - from 6 to 9 then from 9 to 12 – resulted in less evident gains of 10.3% and 4.4%, respectively. Beyond 12 nodes, the effect on the accuracy was insignificant.

Fig. 10 also shows a trend of accuracy improvement with using two hidden layers rather than one (The resulting average improvement is 10.1%). This effect was particularly evident in networks with a small number of hidden nodes (3 or 6) and reduced rapidly with 9 or more nodes. With more hidden nodes, it became successively more difficult to justify using two hidden layers especially when considering the large increase in training time associated with this change in network architecture.

The other parameter that was studied in fig. 10 was the transfer function. Overall, there was little difference between the results



(a) Assessment of network built with different architectures

(b) Comparison between the target loads and the network predictions for the case with 9 nodes in 1 hidden layer and with the tanh function

Fig. 10. Assessment of neural network trained to choose optimum profile and dimensions of cold-formed sections.

of the two functions that could support using one of them over the other.

8. Assessment of design neural networks second strategy

The inability of the first design network to produce accurate results demonstrated a need for an alternative strategy. The second strategy attempted herein involved two steps:

• First, a network trained with data related to all four profiles was used to choose the optimum profile.

• Second, one of four small networks each trained with data related to only one profile, was used to choose the optimum *dimensions*.

The first network was built first and the accuracy of its results in choosing the optimum profile was assessed in fig. 11. Although using two hidden layers resulted in some improvements, the accuracy with a single hidden layer and with 9 or more hidden nodes was still at an adequate level (with average errors around 5%).

The four small design networks were then built and assessed in the same way in fig. 12. Notice that the number of hidden nodes could not be increased beyond 9 in the plain channel network in order to avoid the overfitting problem as explained above. Again with 9 or more hidden nodes, the average errors were below 5% in all cases, except for the plain channel network. In this case, the relatively small number of members in its training database (93) left wider gaps in its training and this in turn led to less accurate predictions especially in the areas within the gaps and outside the training region. The distribution of the results for the four networks for the cases with 9 nodes in a single hidden layer and with the tanh function are also presented in fig. 13 and shown to be within a small error range in most cases.

The interesting point now is to examine the performance of the whole design tool made up of all five networks as described above and shown in fig. 9. In this case, the assessment is limited to the networks with 9 nodes in a single hidden layer and with the tanh function. This architecture was found to represent the best compromise between accuracy and training cost. With these networks, the average error in choosing the optimum profile was about 5%. In the cases where the optimum profile was selected, the average error in choosing the optimum dimensions was below 5% (except with plain channel members). Then in cases where the optimum profile was not selected, the cross-section chosen in the second step was in most

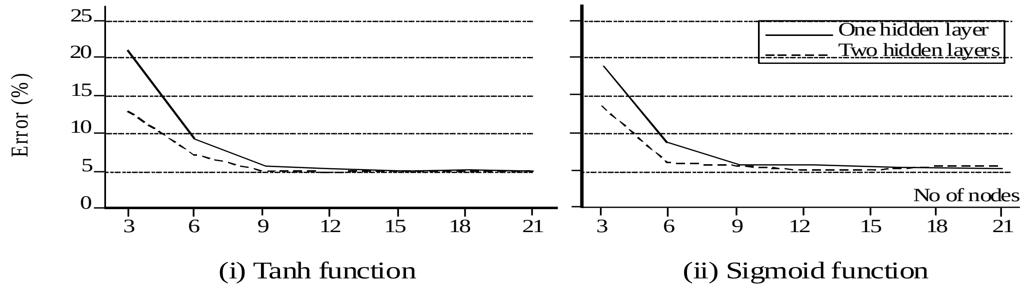


Fig. 11. Assessment of neural network trained to choose optimum profile of cold-formed sections.

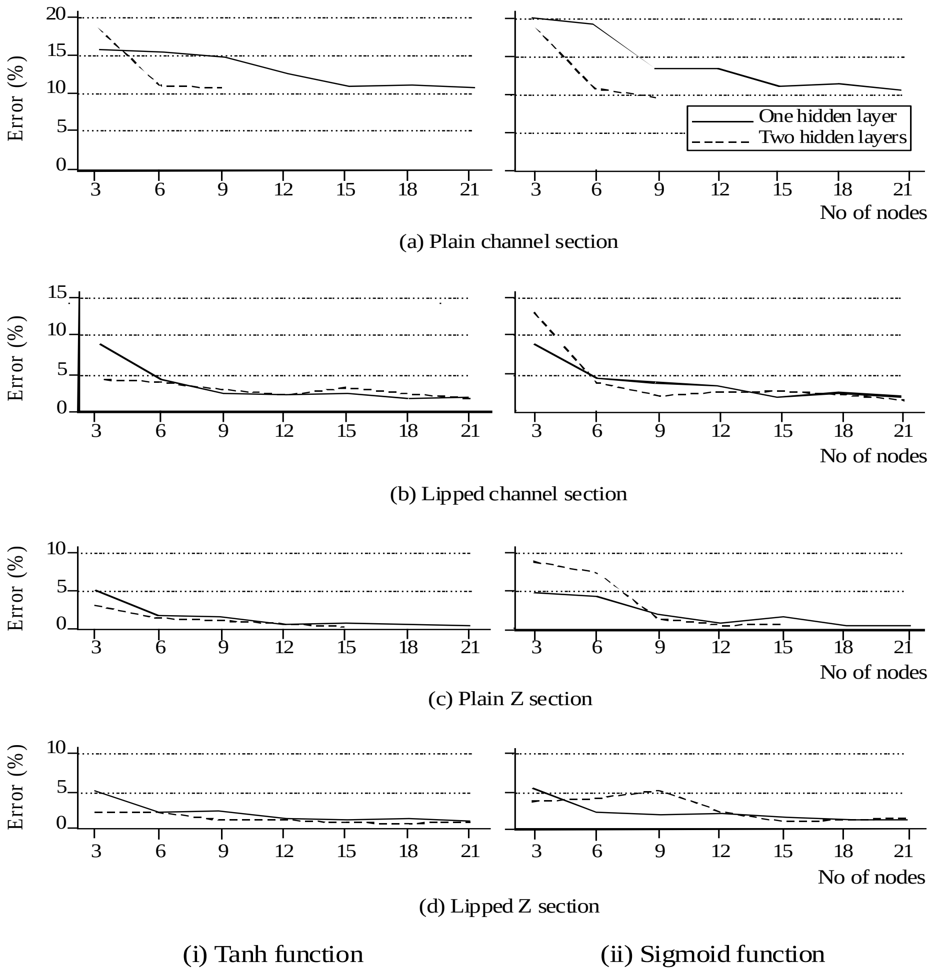


Fig. 12. Assessment of neural network trained to choose optimum dimensions for C and Z sections.

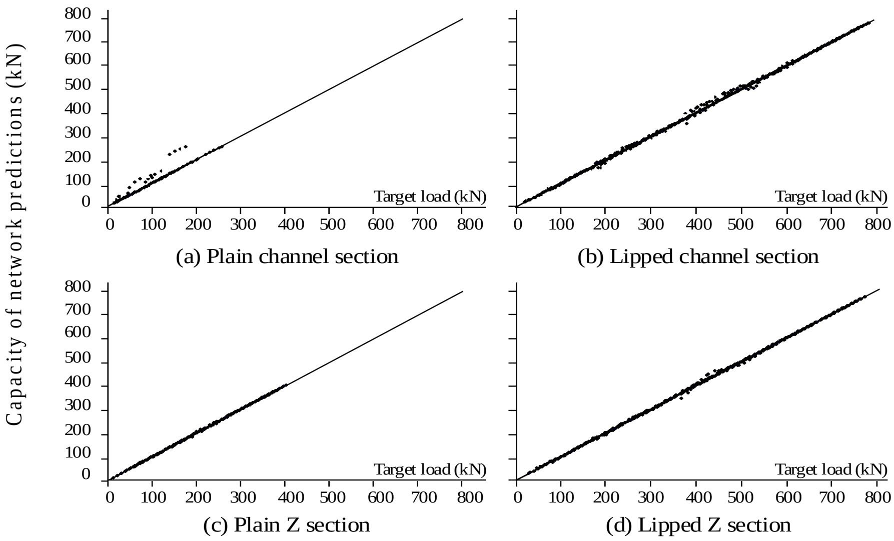


Fig. 13. Assessment of neural network trained to choose optimum dimensions for C and Z sections for the case with 9 nodes in 1 hidden layer and with the tanh function.

cases quite close to the optimum section, with the average error again remaining below 5%. Inspection of cases where the optimum profile was not selected reveals that these cases were close to the boundaries between the optimum performance areas of different profiles, which might explain why the sections chosen in the second step were quite close in efficiency to the optimum sections.

9. Network operation

The parametric study presented above was intended to improve understanding of how the network architecture influences the accuracy. There is strong evidence that with more hidden nodes and hidden layers, the accuracy improves. However, this is also associated with an increase in the cost of training the network. The decision on which architecture to choose should be left to the users who can decide based on their accuracy requirements and perhaps hardware capabilities. In any case, the cost of having a complex architecture mainly applies to the training step, as once the network is trained, its operation becomes extremely fast and straightforward regardless of its architecture.

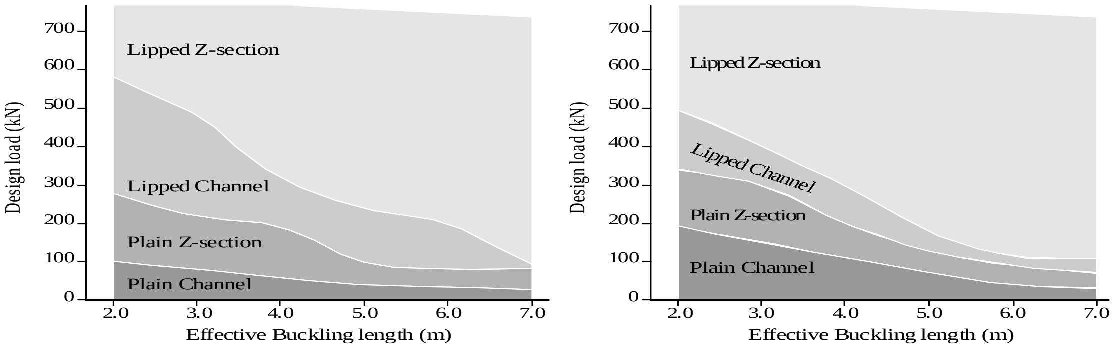
In this work, a choice of a single hidden layer with 9 nodes was thought to yield a good compromise between accuracy and cost. The second strategy, with a profile network and four small design networks, was also preferred for the reasons outlined above.

The trained networks could be used to choose the optimum profile and dimensions for a particular design problem. They could also be used to give an overall view of when each section type is expected to be most efficient. This problem was used in this work to demonstrate the power of the tool developed above. The researchers concentrated on the design of cold-formed steel members with length between 2m and 7m and under a compression load between 0 and 800kN. The network was trained twice, with two different combinations of efficiency criteria:

a. with only the strength: weight ratio as before (100% Q/W), and

b. with a combination of the strength : weight ratio and the strength: cost ratio (40% Q/W + 60% Q/C).

The same procedure for preparing the training database and for training the network as explained in this paper was followed. The results of the designs in these two cases are plotted in fig. 14. While these results demonstrate the usefulness of the design tool, they could themselves be used as design guides for cold-formed steel designers.



(a) Results with a single efficiency criterion (Q/W)

(b) Results with two efficiency criteria (40% Q/W + 60% Q/C)

Fig. 14. Optimum profiles with two efficiency criteria.

10. Conclusions

From the work conducted and presented in this paper, it is evident that a reliable tool for the optimum design of cold-formed steel members can be built using neural network technology. By learning from a wide range of solved examples, the neural network tool can consider all practical possibilities and effectively arrive at the optimum section for a new application. The tool is easy to use and can produce quick and reliable designs once it has been trained. Further, the following conclusions can be drawn from the results presented in this paper:

1. In designing a section, it is best to use two networks in a row; one to choose the profile that is most likely able to produce the best performance and another to choose the dimensions. This strategy is proven better than using one network to conduct both design steps.
2. Increasing the number of the network's hidden layers to two is not justifiable because of the resulting slight change in network accuracy and the subsequent slow speed of network training. This is particularly true in networks with 9 or more nodes per hidden layer.
3. At least 9 nodes should be used per hidden layer in order to maintain a high accuracy. With more hidden nodes, the network accuracy is expected to improve gradually. However, there is usually little advantage gained in using more than 15 nodes.
4. Changing the transfer function results in inconsistent effects on the network accuracy, and therefore no firm conclusion could be reached on which function should be used.
5. It is essential that the knowledge database used to train neural networks cover all practical areas of application. Where gaps exist in the training set, the network accuracy is expected to show notable deterioration.

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