Design and Development of Ships Using an Expert System Applying a Novel Multi-layered Neural Networks

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ABSTRACT: In this paper a neural network was designed and tested for estimating the cost of the activities and the hours of the activities in the shipping industry, by considering the ship parameters such as length of the ships, width, tonnage, etc. Multi-layered feed forward neural network trained by back-propagation algorithm was used in that work. Its results encouraged the research team to develop a new neural network model for representing also the indirect cost of ship construction. A neural network model was configured also for establishing the relationship between the cost of the activities and the indirect costs. The new network was trained by using data of eighteen different ships in order to finalize the design of four new ships.

The work reported in this paper a totally a different concept viz., that a new expert system is developed using a multi-layer neural network. This is the first time an expert system is developed using a neural network as its core and the first time a multi-layer neural network has been constructed and tested successfully.

1 INTRODUCTION

A review of Artificial Neural Network (ANN) applications indicated that such networks could provide a mechanism for accumulating historical data and be used to aid decision making process (Ziarati, 2003). However, of equal importance, if not more, is the ANN capability of allowing cost relationships to be determined in shipbuilding industry. The first task was either to identify an existing ANN or to develop one for knowledge acquisition and presentation of the intended model. The literature search led to an existing neural network (Ziarati et al, 2002);(Ziarati et al,2003) which had been used successfully elsewhere.

Inputs  

Data  

MODEL  

ARITHMETIC  

MATHEMATICAL AND/OR  

NUMERICAL  

Outputs  

Activity Costing  

Time Taken  

Cost Relationships

Figure 1. The Basic System for establishing production activities (Source: Ziarati, 2003)

The above ANN (Figure 1) is designed to carry out two basic tasks. The first task establishes a relationship between the cost of the activities for a
ship and ship’s identity parameters such as length, width etc. The second task establishes a relationship between the activity periods for constructing a ship and again identity parameters as before. General block diagram of ANN is shown in Figure 2.

![Figure 2. General Block Diagram of the ANN (Source: Ziarati 2003)](image)

The research overall is concerned with the development of identifying activities in building a ship and computing activities times and the direct costs of each activity. The ultimate aim of this work is to design and develop a more reliable costing model for building ships. Activity costs of the ships were calculated by respecting the Activity Based Costing (ABC) technique. (Beajon, and Singhal, 1990); (Gary, 2001); (Ozbayrak et al, 2004).

2 NEURAL NETWORK FOR COMPUTING THE DIRECT COSTS OF THE ACTIVITIES IN SHIP BUILDING

This artificial neural network undertakes two basic tasks, it establishes the relationship between the:

i) cost of the activities for a ship and the identity parameters of the ship , e.g. length, width, tonnage, etc., and

ii) hours of the activities for a ship and the identity parameters of the ship.

From both application the same network architectures shown in Figure 1 was used. The ANN has the following properties:

a) Consists of multiple neurons.

b) There are three layers termed ‘input’ layers, ‘hidden’ layers and ‘output’ layers. The number of neurons at the ‘input’ layer must be equal to the number of input parameters so that each ‘input’ is represented by a given neuron. In the work presented here there are 11 input parameters. Each input parameter represents a specific property such as ‘length of the ship’, ‘width of the ship’, etc. Since there are 11 input parameters, the number of the nodes for the input layer of the network is also 11 in order that the above rule is satisfied.

c) There are no restrictions or analytical formula for the number of nodes in a hidden layer. It has been set to 20 nodes.

d) For the output layer, the number of neurons must be equal to the number of output parameters since each node represents an output parameter. There are 395 activities for ships being tested here. Therefore, the number of the neuron in the neural network has been set to 395.

e) Neural networks process the normalised values of the input parameters and produce the normalised values of the output parameters.

f) The neural network must be trained enabling reliable relationships between input and output parameters to be established. Although there are several training methods, the most common method, i.e. back-propagation, is used for these neural networks. The main aim in the back-propagation learning algorithm is to achieve minimum Sum Square Error.

2.1 Discussions and Conclusions

Figure 3 demonstrate that neural network reached a steady state after some 9000 epochs, reaching a tolerance error of less that 0.001 hence providing a stable system for the intended experiments. The Figure 4 shows the regression line representing the relationship between original training data and neural networks output. As can be seen for ship 1 the two sets of data converge and have strong and positive correlation. The second figure shows relative and average % error for all the 395 activities in constructing the first ship. Similar experiments were carried out with the other four ships.

The results are promising, clearly showing that neural network can reliably be used to predict the cost of each activity in building a vessel and also forecast the time taken for each of these activities. Similar experiments were carried out for the four ships. Full activity charts identifying cost of activities and time taken for each of these activities for all seven ships are available but due to the shear size of these charts, these are not presented in this paper but given in (Urkmez at al., 2007).

The results obtained were used in the construction of the two new vessels. The research work is continuing and is expected the work would lead to improved data gathering system enhancing the quality of the data. In parallel the neural network developed as part of this research programme is being incorporated into a knowledge-based-system with a view to improve the quality and reliability of forecasted activity costs and activity time as well as
ability to predict lead-times and project management of ships built in the future.

Figure 3. Changes in error during training of neural networks.

3 NEURAL NETWORK MODEL NETWORK MODEL FOR DEVELOPED FOR COMPUTING THE INDIRECT COSTS

The earlier neural network model was reconstructed as shown in Figure 5. The network this time has four layers; input layer, pre-processing layer, main hidden layer and output layer. It has two hidden layers; the first hidden layer is called as pre-

processing layer and the connection structure between the input layer and this pre-processing layer is not fully-connected. These connection structure decreases the number of the elements of the weight matrix between these layers from 77 to 27.

Figure 5. Neural network structure for predicting the indirect costs.

Similar ANN structure has been used for forecasting the shipping demand in (Akdemir B. et al, 2008). The Neural network model estimates the indirect costs of the ships considering the ship parameters. There are 11 defined parameters to identify the ships. These parameters are classified into three groups such as manufacturing parameters, geometric parameters and capacity parameters as shown in Table 1.

Table 1. Input parameters of the ships

<table>
<thead>
<tr>
<th>MANUFACTURING PARAMETERS</th>
<th>GEOMETRIC PARAMETERS</th>
<th>CAPACITY PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>Value</td>
<td>Parameter</td>
</tr>
<tr>
<td>Company Name</td>
<td>0, 0.5, 1</td>
<td>LOA</td>
</tr>
<tr>
<td>Type of the Ship</td>
<td>0,0.25,0.5,1</td>
<td>LBP</td>
</tr>
<tr>
<td>Order Number</td>
<td>1-7</td>
<td>BM</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DM</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum Draught</td>
</tr>
</tbody>
</table>

This neural network has been designed to produce the indirect costs at the output layer for a given ship parameters at the input layer during training by using back propagation algorithm. Data of the 18 ships has been used for training of ANN. Input parameters are shown in Table 2. and the output parameters, in the other word, indirect costs are shown in the Table 3.
Table 2. Input parameters of 5 ships selected from the 18 ships used for training of ANN.

<table>
<thead>
<tr>
<th>INPUT PARAMETERS</th>
<th>COMP</th>
<th>TYPE</th>
<th>Order</th>
<th>LOA (m)</th>
<th>LBP (m)</th>
<th>BM (m)</th>
<th>DM (m)</th>
<th>Max Draught (m)</th>
<th>ENGP (Kwh)</th>
<th>Speed</th>
<th>DWT</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB 188</td>
<td>NB 201</td>
<td>NB 203</td>
<td>NB 204</td>
<td>NB 205</td>
<td>NB 212</td>
<td>NB 218</td>
<td>NB 220</td>
<td>NB 95</td>
<td>NB 212</td>
<td>NB 218</td>
<td>NB 220</td>
</tr>
<tr>
<td>COMPANY</td>
<td>ADIK</td>
<td>ADIK</td>
<td>TORGEM</td>
<td>ADIK</td>
<td>ADIK</td>
<td>ADIK</td>
<td>ADIK</td>
<td>ADIK</td>
<td>ADIK</td>
<td>ADIK</td>
<td>ADIK</td>
</tr>
<tr>
<td>TYPE</td>
<td>CHM</td>
<td>MP</td>
<td>BC</td>
<td>CHM</td>
<td>CHM</td>
<td>CHM</td>
<td>CHM</td>
<td>CHM</td>
<td>CHM</td>
<td>CHM</td>
<td>CHM</td>
</tr>
<tr>
<td>Order</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>LOA (m)</td>
<td>122.66</td>
<td>126.08</td>
<td>186.45</td>
<td>122.66</td>
<td>122.66</td>
<td>145.6</td>
<td>122.66</td>
<td>147.5</td>
<td>107.34</td>
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<td></td>
</tr>
<tr>
<td>LBP (m)</td>
<td>116.08</td>
<td>113.75</td>
<td>177</td>
<td>116.08</td>
<td>116.08</td>
<td>134.28</td>
<td>116.08</td>
<td>140</td>
<td>101.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BM (m)</td>
<td>17.2</td>
<td>20</td>
<td>30</td>
<td>17.2</td>
<td>17.2</td>
<td>22.6</td>
<td>17.2</td>
<td>22.4</td>
<td>15.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DM (m)</td>
<td>8.8</td>
<td>10.4</td>
<td>16.2</td>
<td>8.8</td>
<td>8.8</td>
<td>11.3</td>
<td>8.8</td>
<td>12.6</td>
<td>8.25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max Draught (m)</td>
<td>6.86</td>
<td>8.08</td>
<td>11.48</td>
<td>8.86</td>
<td>8.86</td>
<td>8.4</td>
<td>8.86</td>
<td>9.8</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENGP (Kwh)</td>
<td>3840</td>
<td>4790</td>
<td>7100</td>
<td>3840</td>
<td>3840</td>
<td>3480</td>
<td>3840</td>
<td>5300</td>
<td>2620</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed</td>
<td>14</td>
<td>14</td>
<td>14.5</td>
<td>14</td>
<td>14</td>
<td>18</td>
<td>14</td>
<td>14</td>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DWT</td>
<td>8100</td>
<td>9300</td>
<td>42000</td>
<td>8100</td>
<td>8100</td>
<td>12750</td>
<td>8100</td>
<td>18000</td>
<td>6000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Manufacturing parameters are consisting of three parameters such as company name, type of the ship and the order number. The parameter, “Company name” can take three different values since we took the data from three shipbuilding company. These company names were coded as 0, 0.25 and 1.0 respectively.

The parameter, “Type of the ship” represents manufacturing purpose of the ship. It can take four different values such as chemical tanker, multi purpose ship, container and bulk carrier. These ship types were coded as 0, 0.25, 0.5 and 1 respectively. If a shipbuilding company build a few ships with same design, cost of the first ship is more expensive than the later ships. For this reason, the other manufacturing parameter order number is an important parameter to affect the costs.

Input parameters and the actual indirect costs of the ships which are used in test phase of ANN are shown in Table 4., Table 5., respectively.
ANN results for activity costs of the ships used in test phase are given in Table 6. ANN performance is shown in Table 7, and Figure 6, by comparing the actual indirect costs of ships and ANN predictions.

4 CONCLUSIONS

The results are promising, clearly showing that neural network can reliably be used to predict the cost of each activity in building a vessel and also forecast the time taken for each of these activities. Similar experiments were carried out for the four ships. Full activity charts identifying cost of activities and time taken for each of these activities for all seven ships are available but due to the sheer size of these charts, these are not presented in this paper but given in Urkmez (2007).

The results obtained were used in the construction of the two new vessels. The research work is continuing and is expected the work would lead to improved data gathering system enhancing the quality of the data. In parallel the neural network developed as part of this research programme is incorporated into a knowledge-based-system which has improved the quality and reliability of forecasted activity costs and activity time as well as ability to predict lead-times and project management of ships built in the future.

Furthermore it is now feasible to conclude all activity costs, both direct and indirect before a ship is constructed. The reliable estimation of indirect costs is helping the ship builders participating in this programme of research to have a better understanding of activity costs and hence enable them to make appropriate decisions in design and manufacturing as well as management processes.

REFERENCES


Figure 6. Comparing the results of ANN and actual indirect costs.

a- Purchasing and logistics costs
b- Design costs
c- Supervision and production control costs
d- Bookkeeping and accounting costs
e- Maintenance and administrative costs
f- Customer relationships costs