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

SUALP URKMEZ
Furtrans, Istanbul,Turkey

REZA ZIARATI & ERDEM BİLGİLİ
TUDEV/Piri Reis Univesity, Istanbul, Turkey

MARTIN ZIARATI
C4FF, Coventry,UK

DAVID STOCKTON
De Montfort University, UK

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.

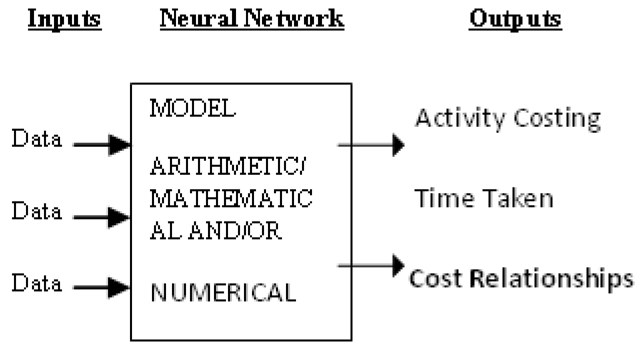


Figure 1. The Basic System for establishing production Activities Time Taken and costs (Source: Ziarati, 2003)

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.

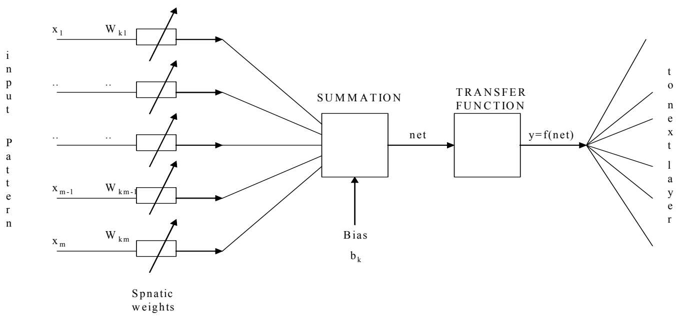


Figure 2. General Block Diagram of the ANN (Source: Ziarati 2003)

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 Activitiy 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 number of the 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. Similiar 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.

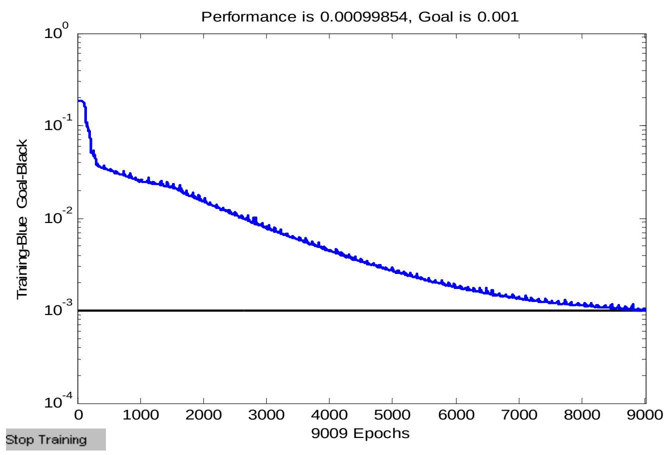


Figure 3. Changes in error during training of neural networks.

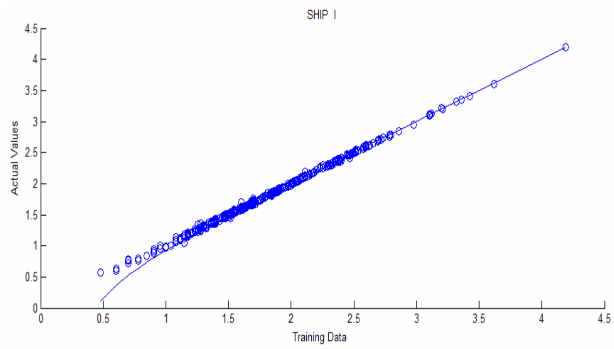


Figure 4a. Regression Line for training data Vs. Actual output values where M is gradient and C is point of intersection for the regression analysis.

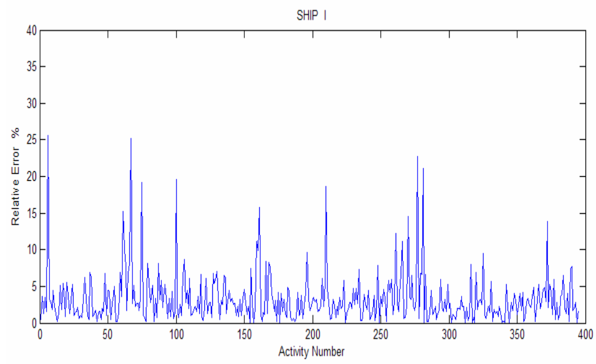


Figure 4.b. Relative Errors Vs. Activities

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

The earlier neural network model was re-constructed 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.

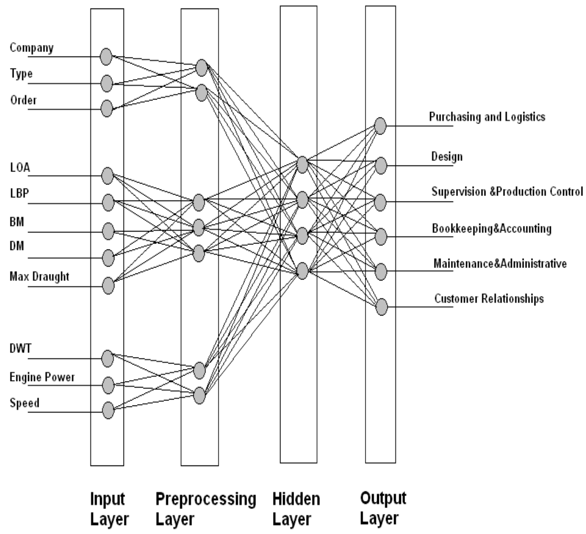


Figure 5. Neural network structure for predicting the indirect costs.

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

MANUFACTURING PARAMETERS		GEOMETRIC PARAMETERS		CAPACITY PARAMETERS	
Parameter	**Value**	**Parameter**	**Value Unit**	**Parameter**	**Value Unit**
Company Name	0, 0.5, 1	LOA	meters	DWT	Dwt
Type of the Ship	0,0.25,0.5,1	LBP	meters	Engine Power	Kwatt
Order Number	1-7	BM	meters	Speed	Knot
		DM	meters		
		Maximum Draught	meters		

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.

		1	2	3	4	5
		NB 188	**NB 201**	**NB 203**	**NB 204**	**NB 205**
INPUT PARAMETERS	**COMPANY**	ADIK	ADIK	TORGEM	ADIK	ADIK
	TYPE	CHM	MP	BC	CHM	CHM
	Order	1	1	1	2	3
	LOA (m)	122.66	126.08	186.45	122.66	122.66
	LBP (m)	116.08	113.75	177	116.08	116.08
	BM (m)	17.2	20	30	17.2	17.2
	DM (m)	8.8	10.4	16.2	8.8	8.8
	Max Draught(m)	6.86	8.08	11.48	6.86	6.86
	ENGPOWER (Kwh)	3840	4790	7100	3840	3840
	Speed (Knots)	14	14	14.5	14	14
	DWT	8100	9300	42000	8100	8100

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.

Table 3. Indirect costs of the ships used for training ANN

		1	2	3	4	5
		NB 188	**NB 201**	**NB 203**	**NB 204**	**NB 205**
INDIRECT COSTS-TL	**Purchasing& Logistics**	125,625	133,075	314,825	123,950	122,250
	Design	125,750	230,610	681,510	117,060	103,300
	Supervision& Prod. Control	653,250	691,990	1637,090	644,540	635,700
	Bookkeeping& Accounting	452,250	479,070	1133,370	446,220	440,100
	Maintenance& Administrative	854,250	904,910	2140,810	842,860	831,300
	Costumer Relationships	75,375	79,845	96,895	74,370	73,350

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.

Table 4. Input parameters of the ships for test stage of ANN

	T1	T2	T3	T4
	NB 212	**NB218**	**NB 220**	**NB 95**
COMPANY	ADIK	ADIK	ADIK	TORGEM
TYPE	CON	CHM	CHM	CHM
Order	6	7	4	2
LOA (m)	145.6	122.66	147.5	107.34
LBP (m)	134.28	116.08	140	101.6
BM (m)	22.6	17.2	22.4	15.8
DM (m)	11.3	8.8	12.6	8.25
Max Draught(m)	8.4	6.86	9.8	6
ENGPOWER (Kwh)	9480	3840	5300	2620
Speed (Knots)	18	14	14	13
DWT	12750	8100	18000	6000

Table 5. Real indirect costs of the ships for test stage

		T1	T2	T3	T4
		NB212	**NB218**	**NB 220**	**NB95**
INDIRECT COSTS (TL)	**Purchasing& Logistics**	190,700	118,125	217,425	120,975
	Design	121,960	96,750	188,790	195,730
	Supervision& Production Control	991,640	614,250	1130,610	629,070
	Bookkeeping& Accounting	686,520	425,250	782,730	435,510
	Maintenance& Administrative	1296,760	803,250	1478,490	822,630
	Costumer Relationships	82,420	70,875	85,455	72,585

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.

Table 6. Indirect costs of the ships predicted by ANN

		T1	T2	T3	T4
		NB212	**NB218**	**NB 220**	**NB95**
INDIRECT COSTS (TL)	**Purchasing& Logistics**	192,851	116,005	213,612	122,852
	Design	120,024	98,603	184,129	198,215
	Supervision& Production Control	995,352	610,114	1132,211	632,060
	Bookkeeping& Accounting	691,520	428,250	779,615	434,247
	Maintenance& Administrative	1302,760	806,514	1485,414	818,746
	Costumer Relationships	81,386	71,240	83,289	72,001

Table 7. Absolute percentage error between the ANN outputs and the real costs

ABSOLUTE PERCENTAGE ERROR		T1	T2	T3	T4
		NB212	**NB218**	**NB 220**	**NB95**
INDIRECT COSTS ERROR (%)	**Purchasing& Logistics**	1.128	1.795	1.754	1.552
	Design	1.587	1.915	2.469	1.270
	Supervision& Production Control	0.374	0.673	0.142	0.475
	Bookkeeping& Accounting	0.728	0.705	0.398	0.290
	Maintenance& Administrative	0.463	0.406	0.468	0.472
	Costumer Relationships	1.255	0.515	2.535	0.805

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 shear 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

Gary Cokins 2001. *Activity-Based Cost Management: An Executive's Guide*, ,ISBN:0-471-44328-X, John Wiley & Sons Inc., US.

Ziarati, M., Stockton D., Ucan, O. N., Bilgili,E. *2002* Application of Artificial Neural Networks in Logistics Systems.*FSSCIMIE'02,ITU, Istanbul, Turkey, 29-31 May.*

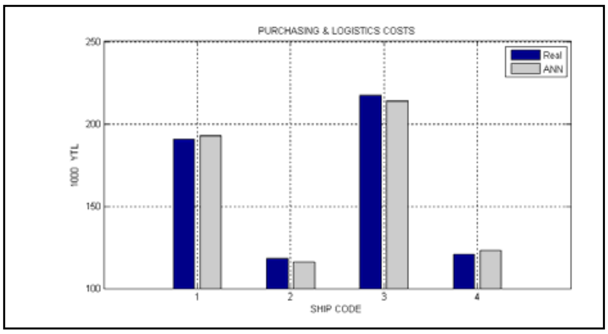
Ziarati, M., Stockton D., Bilgili,E., Ucan, O. N. 2003. The Next Generation Of Enterprise Resource Planning (ERP) Systems Incorporating A Neural Network Forecasting Tool. *Proceedings of the 7th INES* , Assiut-Luxor, Egypt March, ISSN:1562-5850.

Ziarati M, 2003. *Improving the Forecasting Process in the Automotive After-Market Supply Chain.* PhD Thesis, De Montfort University,

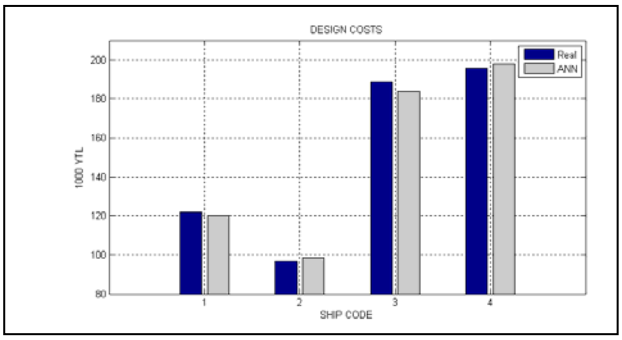
UK.Ozbayrak, M., Akgun, M., Turker, A.K. 2004. ABC estimation in a push/pull advanced manufacturing system, *International Journal of Production Economics*, Vol.87 pp.49-65.

Urkmez S., Stockton D., Ziarati,R., Bilgili,E. 2007. Activity Based Costing For Maritime Enterprises. *ICMR 2007,* De Monfort University,Leicester,UK. 11-13, September.

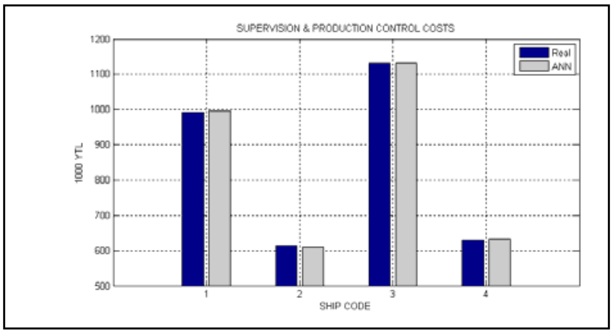
Akdemir B., Bilgili E., Ziarati M., Stocton D. 2008. Supply and Demand in Shipping Market Using Intelligent Neural Networks, IMLA 2008, Izmir, Turkey.



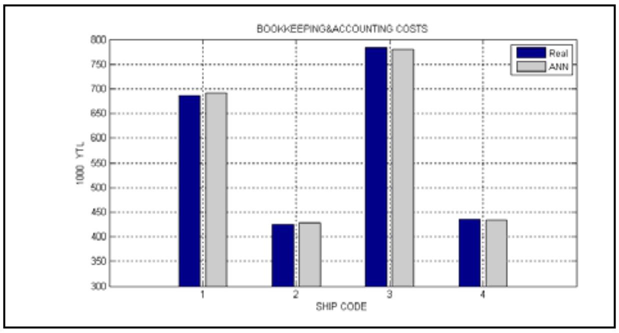
a- Purchasing and logistics costs



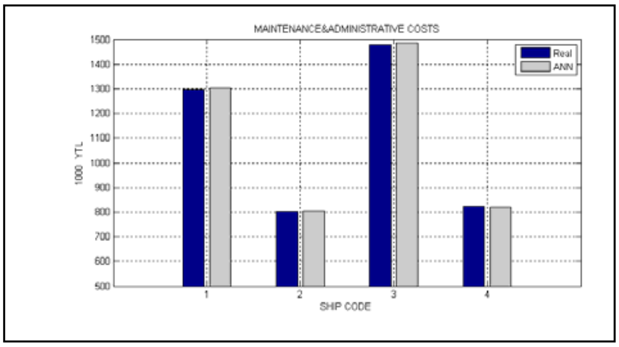
b- Design costs



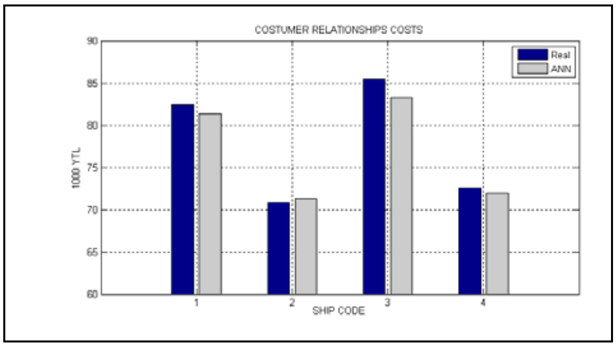
c- Supervision and production control costs



d- Bookkeeping and accounting costs



e- Maintenance and administrative costs



f- Costumer relationships costs

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