Predicting Demand for Products as Part of Intelligent Enterprise Resource Planning

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ABSTRACT

Most Enterprise Resource Planning (ERP) systems are based on old Material Resource Planning (MRP) II philosophy and do not have facilities for intelligent assessment of the market place. In this paper, we have proposed a novel means of developing Intelligent Enterprise Resource Planning (IERP) systems. Accurately forecasting demand for a given product is a pre-requisite for any effective 'Pull' based intelligent ERP system. Here, 'Pull' means producing products based on actual demand and intelligence means the prediction system is capable of learning from the past trends and exercising choice which helps in decision support system.

Most companies, with or without ERP, either carry out an thoughtful assessment of the market before deciding on the number of products they should be producing or carry on producing goods, at worst hoping they would sell what they produce or at best, use conventional forecasting methods. What is of significance in deciding on the number of products which to be made is the accurate prediction of demand for these products. Research has shown that forecasting techniques using neural networks result in most accurate forecasts. It has also been demonstrated that Neural Networks if optimised could even produce more accurate predictions.

To date, all forecasting systems developed have been based on Artificial Neural Networks (ANN) and the cellular neural networks (CNN) have not been used. The argument has been that CNNs cannot cope with time series applications and are known and reported to be suited for where there is a cellular relationship among a set of data.

This paper reports on the outcome of a recent research on the application of new cellular neural network and the comparison of results with an optimised ANN. In the first experiment, both these neural networks were used to establish relationship between inputs and outputs of the same two sets of data. In the second experiment, the same two networks were used in completely different forecasting application and the results of CNN based system, in both cases, were shown to be more accurate than ANN results.

The CNN was then incorporated in an existing ERP system and found to function well and hence consider suitable for applications in Intelligent ERPs.

The CNN is a 3-Dimensional and is the first 3-D forecasting system reported in literature studied to date.

Keywords— 3D Neural Networks, Artificial Neural Networks (ANN), Cellular Neural Networks (CNN), Genetic Algorithm (GA), Neural Network Applications.

1. Introduction

It is important to state why the results presented in this paper are so important. The research reported in this paper is to improve the predictability of forecasting methods as current methods are considered unacceptable. In the shipping for instance even most accurate results were found not to be acceptable (Akdemir, 2012). Even with accuracies of some 2% which is more than acceptable for predicting demands or rates for a given product or commodity, in majority of cases studied, in shipping 2% could mean some 15 new large vessels. Akdemir (2012) states that in bulk shipping a 4% error means 4 million DWT capacity which is equivalent to some 31 capesize vessels (each capsize vessel is equivalent to 130,000 dwt).

The research reported in this paper is a continuation of the Factories of the Future programme instigated in the early 1980s supported by the EU. The programme initially concerned aspects relating to high technology manufacturing with emphasis on automation cited in [1] and [2]. The programme became more focused on system integration and development of information management systems in ERPs in the 1990s (EUREKA (QMIS/IBIS, 1990-95) concentrating on the development of an integrated business information system [3]. Early in the 2000s, the Factories of the Future programme put a great deal of effort into wireless communication [4-5], roadmap development [6] and value stream mapping [7], helping the manufacturing industry to be leaner and become more efficient. In the mid 2000s focus was diverted into a new concept now known as ‘Lean Optimal’ [8]. The development of the lean optimal system led to the development of the 3-Dimensional Neural Network referred to in this paper as 3-DCNN. It was noted that general 2-D CNN commonly used structure is not suitable for forecasting application. Therefore, the CNN was later developed into a 3 dimensional network. The recent work by Urkmez et al [9] (and [10]) also led to the development of multi-hidden layer ANNs. The following sections give a summary of the 3-DCNN and make references to the multi hidden layer ANN, and the new 3-DCNN. The 3-DCNN and the optimised ANN are then given the task of predicting the demand for a given type of ship and later to forecast the indirect cost of building a ship. The predicted results of 3-DCNN are more accurate that the ANN results. Since CNN are by far more efficient than ANN, the results clearly suggest that CNN could be future means of forecasting demand for products in the future. The more accurate results of cost estimates, in the second experiment also suggest that CNN could be a major rival for forecasting trends for any time-series variable.

2.1. Artificial Neural Network (ANN)

A good description of this type of ANN is given in [4]. The ANN in 2007 was re-configured by adding additional hidden layers [9-10] making these types of NN much more efficient and reliable. The ANN models reported in the latter references were based on the earlier work by Ziarati, Ucan and Bilgili who published several papers on the subject; a summary of their findings are given in [9-12] and [22]. A typical artificial model of a neuron is shown in Fig. 1. The back-propagated technique was used to train the ANN.

2.2 Cellular Neural Network (CNN)

In 1998 a new kind of artificial intelligence tool was proposed called Cellular Neural Networks (CNN) where the connections between neurons are restricted with their neighbours only [15]. This type of NN is one of the most popularly used and is described in detail later in this paper. The work on the NN led to the development of Genetic Cellular Neural Networks (GCNN).

GCNN is a slight variation of the Cellular Neural Network which includes the application of Genetic Algorithms [20-21]. This network uses less stability parameters than Back Propagation-Artificial Neural Networks (BP-ANN) and hence should be better suited to fast changing scenarios experienced in real distribution systems. Details of GCNN for forecasting demand are provided by Ziarati et al [16].

A general CNN neighbourhood structure is shown in Fig. 2. The CNN structure is well suited for the computation of tabulated inter-related data. The CNN normalised differential state-equation can be described by matrix-convolution operators as follows:

$$\frac{dX}{dt} = -X + A*Y + B*U + I \qquad (2)$$

where U, X, Y are input, state and output of an M x N matrix, while I is an offset vector. The feedback and feed-forward connections are represented by matrix A and B.

2.2.1 Genetic Algorithm (GA)

Genetic Algorithm is a learning mechanism that abides by the rules of genetic science. The algorithm has been successfully applied in a number of cases such as image processing, geophysics, etc. [19] and [22]. It uses a binary coding system to search for optimum values of A, B and I.

The underlying principles of GA were first published by Holland [17]. The mathematical framework was developed in the 1960s and was presented in his pioneering book in 1975 [18]. In optimisation applications, they have been used in many diverse fields such as function optimization, image processing, market research and product marketing, system identification and control and so forth. In machine learning, GA has been used to learn syntactically simple string IF-THEN rules in an arbitrary environment. A high-level description of GA was introduced by Davis. [19]. GA has been used to training the CNN in this programme of research.

3. 3- Dimensional Cellular Neural Network

The development of this Network was started at Dogus University with support from Istanbul University. The Model shown in figure 3 was fully developed at TUDEV Institute of Maritime Studies in 2008 and tested in 2009. The model can be presented as a 3 Dimensional table or a cylinder. In the model used here, CNN is composed of three-dimensional shaped cells. Some cells are placed at the inside of a cylinder. These are called inner cells. The other cells are placed around the cylinder and called the outer cells. In forecasting applications for instance, the outer cells will be used to process the independent variables (demand factors). The inner cells will be used to process the dependent variable s -predicted parameter- i.e. demand for a product. As shown in Figure 4 there are some connections connecting the outer cells to the inner cell. Each horizontal ring represents a special moment in time. 3DCNN has the following dynamics for each inner cell $C_{mn}(k)$. For a given time n, the m^{th} independent variable is represented by $C_{m,n}$ and it is placed at the m^{th} outer cell of the n^{th} time segment. Its state equation is written as follows;

$$\begin{aligned}\frac{dx_{m,n}(k)}{dk} &= -x_{m,n}(k) + A_{outercells}(m,1).y_{m,n-1}(k) + A_{outercells}(m,2).y_{m,n}(k) \\ &+ B_{outercells}(m,1).u_{m,n-1}(k) + B_{outercells}(m,2).u_{m,n}(k) + I\end{aligned} \quad (3)$$

For the inner cell of the segment n;

$$\begin{aligned}\frac{dx_{p,n}(k)}{dk} &= -x_{p,n}(k) + \sum_{r=0}^{p} A_{innercells}(r,1).y_{r,n-1}(k) + A_{innercells}(r,2).y_{r,n}(k) \\ &+ \sum_{r=0}^{p} B_{innercells}(r,1).u_{r,n-1}(k) + B_{innercells}(r,2).u_{r,n}(k) + I\end{aligned} \quad (4)$$

At the steady state condition;

$y_{m,n} = f(x_{m,n})$

where

$x_{m,n}$ is the state of the cell $C_{m,n}$

$u_{m,n}$ is the input of the cell $C_{m,n}$

$y_{m,n}$ is the output of the cell $C_{m,n}$

k is number of iteration

m,n are cell indexes

p is number of the outer cells for any ring. There are $p+1$ cells in each horizontal ring since the index of the inner cell is zero.

f is PWL activation function

$x_{mn}(k)$ is state of m^{th} outer cell for k^{th} iteration at the moment n .

$y_{mn}(k)$ is output of m^{th} cell for k^{th} iteration at the moment n.

$A_{innercells}(m,d=1)$ is weight between an inner cell located at any segment and the output of m^{th} the cell located at previous segment.

$A_{innercells}(m,d=2)$ is weight between an inner cell located at any segment and the output of m^{th} the cell located at same segment.

$B_{innercells}(m,d=1)$ is weight between an inner cell located at any segment and the input of m^{th} the cell located at previous segment.

$B_{innercells}(m,d=2)$ is weight between an inner cell located at any segment the input of m^{th} the cell located at same segment.

$A_{outercells}(m,d=1)$ is weight between the m^{th} outer cell located at any segment and the output of m^{th} the cell located at previous segment.

$A_{outercells}(m,d=2)$ is weight between the m^{th} outer cell located at any segment and the output of m^{th} the cell located at same segment.

$B_{outercells}(m,d=1)$ is weight between the m^{th} outer cell located at any segment and the input of m^{th} the cell located at the previous segment.

$B_{outercells}(m,d=2)$ is weight between the m^{th} outer cell located at any segment and the input of m^{th} the cell located at the same segment.

I : denotes the offset (bias) value of each cell in the network.

4. Training 3-DCNN with GA

3-DCNN must be trained with sample data for obtaining the weight coefficients a_n, b_m and offset coefficient I as has been the case with CNN. In GA applications there are often two equations used. In the first equation, all outputs of the cells are compared to the desired values and the sum squared error is calculated with cost function according to following equation.

$$\cos t_s(a_n, b_{m,} I) = \sum_{m=1}^{T} \sum_{n=0}^{p} (y_{mn} - d_{mn})^2 \qquad (5)$$

where In this application the trend for world fleet (demand of shipping) is predicted using ANN and the new 3-DCNN. The ANN was optimised for this application.

y_{mn} is actual output of the cell C_{mn}

d_{mn} is desired output of the cell C_{mn}

T is number of the segments

p is number of the outer cells

s is chromosome number

In the second equation the fitness value of each chromosome is calculated as;

$$fitness_s(a_n, b_m, I) = \frac{1}{\cos t_s(a_n, b_m, I)} \qquad (6)$$

5. APPLICATION

The purpose of the applications is to accept or reject the hypotheses that 3D-CNN produces more accurate results than an optimised ANN and that this is true in more than one case/application. The cases selected were very different to each other. In one case the experiment relates to predicting the demand for shipping in a given year and in the other, it relates to estimating the indirect cost for building a given type of ship. If these hypotheses are accepted, this clearly indicates a major break through as CNN would be established as the preferred choice for forecasting which would make computation more efficient and reliable.

5.1 Application 1

5.1.1 Application 1 – Optimised ANN

The aim of this application is aimed to predict the DWT world fleet demand in total for the future by considering the historical data of DWT world fleet.

The original data and those obtained by the optimised ANN is shown in Tables 1 and

2. The training of the ANN and optimisation was carried out as in Akdemir et al (2012). Table 1 is the original data extracted from literature. Table 2 shows the results also using Regression technique for referential purposes. Table 3 shows the comparisons of results from Regression and ANN techniques.

5.1.2 Application 1-3DCNN

The aim of this application is the same as for ANN, aimed to predict the DWT world fleet demand in total so that comparison could be made between ANN and CNN accuracy.

In the training stage of 3DCNN, the genetic algorithm finds the optimum values of the matrices $A_{innercells}$, $A_{outercells}$, $B_{innercells}$, $B_{outercells}$ and I . There are 37 parameters to be optimized in this example. Each chromosome in genetic algorithm includes the binary codes of 37 parameters and each chromosome includes 296=37*8 bits since each parameter has been coded with 8 bits. At the beginning of the genetic search 60 random chromosome were created. Then, the best chromosome was found at the 78^{th} generation.

The templates of the best chromosome are;

$$Aoutercell = \begin{bmatrix} 0.531 & -0.325 \\ 0.006 & -0.012 \\ 0.312 & 0.287 \\ 0.319 & 0.281 \end{bmatrix} \qquad (7)$$

$$Ainnercell = \begin{bmatrix} 0.431 & 0.281 \\ -0.087 & 0.606 \\ 0.687 & -0.131 \\ 0.469 & 0.562 \\ -0.381 & -0.519 \end{bmatrix} \qquad (8)$$

$$Boutercell = \begin{bmatrix} 0.431 & 0.281 \\ -0.088 & 0.606 \\ 0.688 & -0.131 \\ 0.469 & 0.562 \end{bmatrix} \qquad (9)$$

$$Binnercell = \begin{bmatrix} -0.275 & -0.619 \\ 0.412 & 0.300 \\ -0.512 & -0.438 \\ 0.688 & -0.788 \\ -0.231 & 0.469 \end{bmatrix} \qquad (10)$$

Original and 3DCNN output data values of this application are presented in Tables 1 and 2 respectively.

5.2. Application 2

In this application a new set of data was obtained. The data related to prediction of indirect cost for building a ship. The ANN, for this application was independently optimised using this time Urkmez (2009) technique as the case for predicting cost was different for predicting demand for shipping.

5.2.1- Application 2 - Optimised ANN

In this application a new ANN model was configured for establishing the relationship between the cost of the activities and the indirect cost parameters of the activities. The new neural network model is a multi-layered, feed forward neural network. It has two hidden layers. The first hidden layer is between the input layer and the second hidden layer; it works as a pre-processor layer and it is not fully connected. The second hidden layer is structured between the pre-processor layer and the output layer. In the input layer, the number of the input neuron is set to the number of the ship parameters. This is because the input nodes are the ship parameters. The neural network model estimates the indirect costs of the ships considering the ship parameters.

There are 11 defined parameters to identify a ship. These parameters are classified into three groups such as manufacturing parameters, geometric parameters and capacity parameters as shown in Table 2.

Manufacturing parameters consist of three parameters such as company name, the 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 companies. These company names were coded as 0, 0.25 and 1.0 respectively.

The parameter, “Type of the ship” represents the 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 builds a few ships with same design, the 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 that affects the costs. Geometric parameters represent the geometric properties of the ships. These five parameters are LOA - length of overall, LBP - length between perpendiculars, BP - breadth moulded, DM - depth ‘moulded’ and maximum draught of the ships. The other parameter group is the capacity parameters and they give the information about the capacity of the ships. These three parameters are DWT – Dead Weight Tonne (tonnage of the ships), engine power and maximum speed of the ship.

There are six defined indirect cost pools during the ship building overall process. These cost pools are: Purchasing and Logistics, Design, Supervision and Production Control, Bookkeeping and Accounting, Maintenance and Administrative and Costumer Relationships.

Data for 22 ships was gathered during the building process from three different shipyards. All of the indirect costs of these ships were distributed to the indirect cost pools which applied the Activity Based Costing (ABC) rules in line with the model developed by Urkmez [12].

5.2.1.1 Neural Network Model

The new ANN model has four layers; the input layer, the pre-processing layer, the main hidden layer and output layer. It has two hidden layers as shown in Figure 4. The first hidden layer is called the pre-processing layer and the connection structure between the input layer and this pre-processing layer is not fully-connected. The connection structure decreases the number of the elements of the weight matrix between these layers from 77 to 27.

This neural network has been designed to produce the indirect costs at the output layer for given ship parameters at the input layer during training by using back propagation algorithms. Data of 18 of the ships has been used for the training of the ANN. The other 4 ships data has been used to test the performance of the ANN.

5.2.1. Application 2 - 3-DCNN Results

Table 4 shows the ship parameters used as input values. The 3-DCNN test results for the four ships are also shown in Table 5 for ease of reference. In this table, ANN and 3-DCNN test results were compared with the actual Activity Base Costs of the ships, then, the absolute percentage error was calculated, as shown in Table 6, to show that 3-DCNN produce more accurate results.

6. Conclusions

6.1. Application 1

It should be noted that the application was chosen at random from several available set of data [9-12]. The comparison of the actual values for World Seaborne tonnage and World Fleet DWT and the predicted values are remarkably good. The results elucidates that the 3DCNN is the most accurate model, it has managed to make the most accurate results with less computation than ANN (Table 4).

The merit of a 3-dimensional network is that it can be arranged to have a specific kind of input for each of its given ring. For example, one of the rings could be the primary values of the input and the next ring could be the secondary values. The same concept can be applied to dependent and independent values.

The difference between CNN and 3DCNN in that the rings forming the cylinder can be the time series for each given values of input and output values.

6.2. Application 2

ANN after being trained was tested with the new data from the four ships not included in the training stage. Absolute percentage error between the new ANN output values and the real costs are shown in Table 6. As shown the neural network produced the indirect costs of these ships at its output layer with an acceptable degree of accuracy.

The results are tabulated in several tables but not shown in this paper. The other five indirect costs such as design costs, supervision and production control costs, book-keeping and accounting costs, maintenance and administrative costs and costumer relationship costs were also computed.

In summary the Absolute percentage errors between the predicted costs of the ANN and the actual indirect costs for the test ships shown in Table 6 clearly shows that the maximum relative error occurred is 2.53 % for the costumer relationship costs of the ship NB 220.

It should be noted that the training of the ANN is similar to existing approaches, but the input values are divided into specific set of data, namely, ship's geometric parameters, capacity parameters and specific manufacturing parameters data. This initial grouping of the data in the ANN has made the resulting relationships between the input and output data much more reliable compared to the current practice [12]. Furthermore, computing has also become much faster. Therefore the grouping of data required additional hidden layers to be added to the neural networks making the output values more reliable.

This concept of group input data can be extended to separate the primary and secondary variables and then further subdivided into dependent and independent values. There has been some experimentation with such approaches by the authors and the results were found to be more accurate and the computing faster than the previous approach of not sub-dividing the input values into groups. Despite all attempts to optimised the ANN and reduce the run time it was not possible to compete with 3-DCNN in both accuracy and in computational efficiency.

In this paper a new 3-dimensional neural network has been designed and tested with good results. The concept of subdividing input values for the ANN into a generic set of data has led to more accurate results and has reduce the computing time but in al cases 3-DCNN produced most accurate results and by far was computationally more efficient.

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FIGURES AND TABLES

FIGURES:

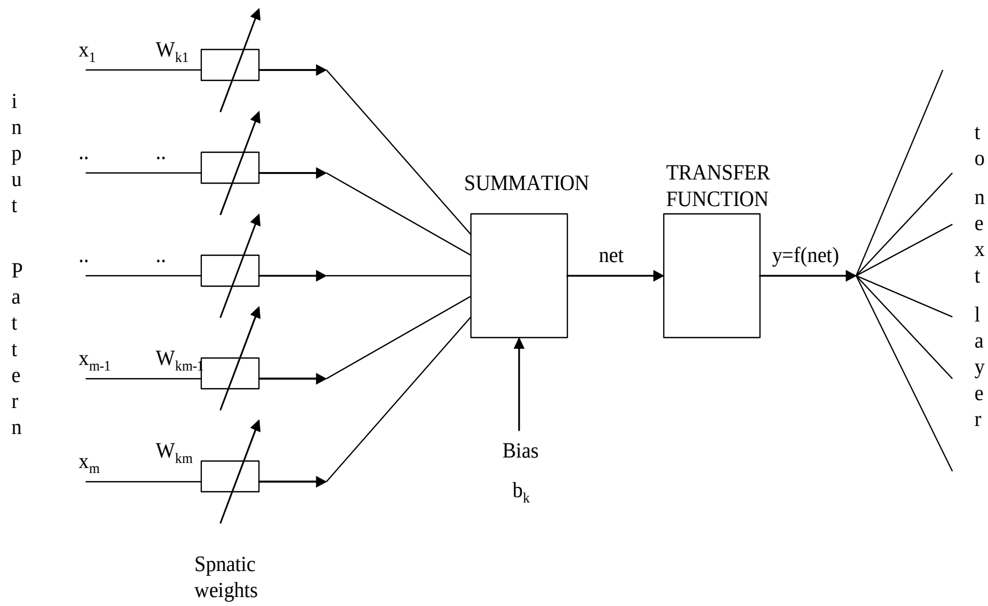
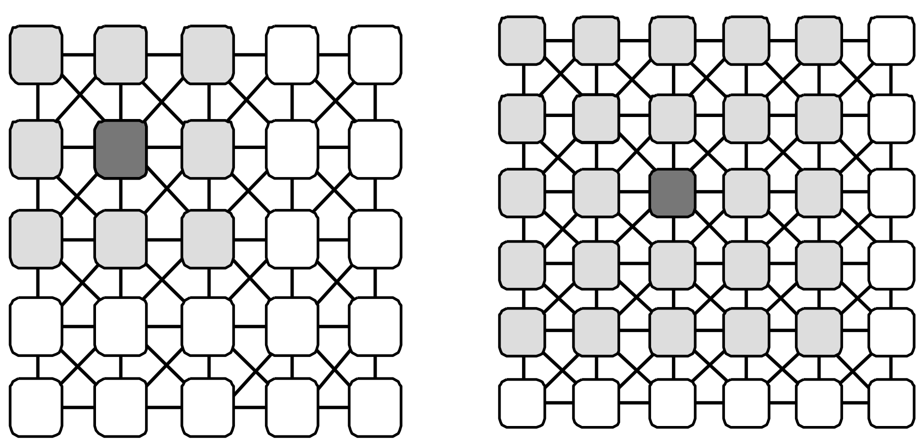


Figure.1. General Block Diagram of a Neuron



r=11 r=2

Figure.2. Cellular Neural Network Structure

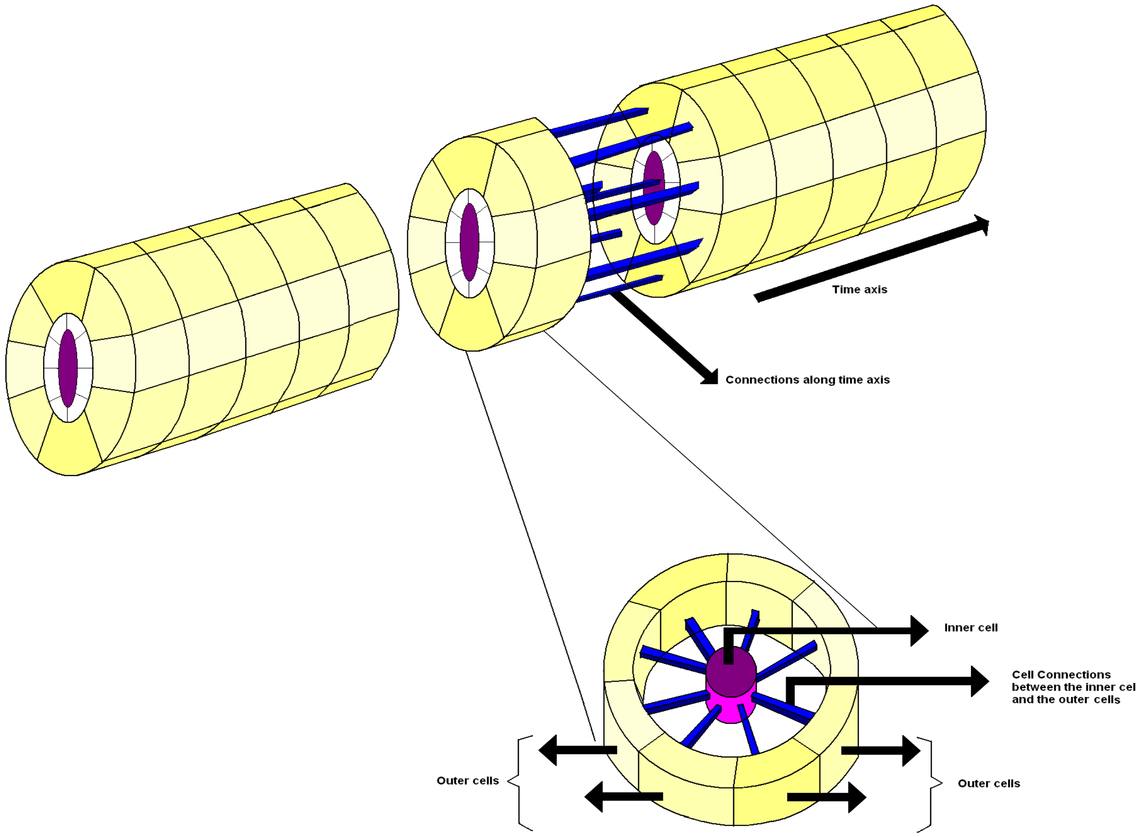


Figure 3. 3D Cellular Neural Network Structure

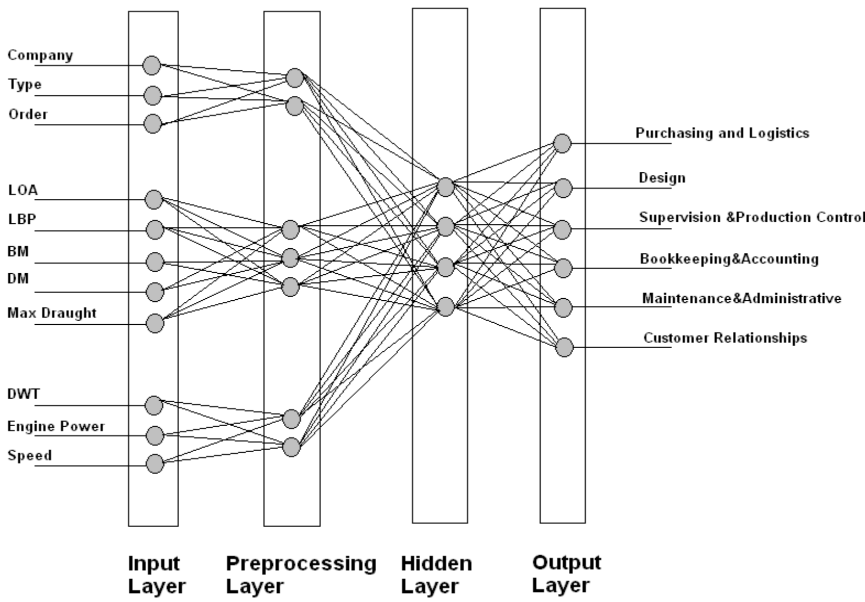


Figure. 4. Neural network structure for predicting the indirect costs

TABLES:

Years	World Seaborne Total Dry Bulk Mil. Tones	World Seaborne Total Bulk Mil. Tones	World Seaborne Grand Total Mil. Tones	World Fleet Total Bulk Mil. DWT	World Fleet Grand Total Mil. DWT
1985	1461	2861	3631	499	**590**
1986	1415	2846	3636	478	**568**
1987	1332	2689	3635	471	**564**
1988	1410	2913	3907	469	**563**
1989	1595	3274	4173	475	**572**
1990	1598	3200	4164	489	**588**
1991	1625	3190	4201	502	**604**
1992	1596	3252	4345	514	**619**
1993	1616	3416	4554	520	**627**
1994	1673	3491	4658	528	**637**
1995	1784	3643	4877	529	**640**
1996	1816	3776	5121	548	**708**
1997	1910	3969	5432	559	**725**
1998	1897	3959	5443	570	**742**
1999	1894	3998	5566	573	**750**
2000	2040	4214	5913	586	**767**
2001	2096	4325	6022	601	**787**
2002	2170	4380	6209	607	**800**
2003	2291	4643	6553	618	**819**
2004	2469	4939	6954	634	**843**
2005	2564	5121	7258	670	**890**
2006	2703	5313	7615	715	**950**
2007	2790	5397	7852	758	**1013**

Table 1. Original data

YEARS	REGRESSION		NEURAL NETWORK		OBSERVED ACTUAL VALUES	
	W.F.Grand Total	VALIDATION	W.F.Grand Total	VALIDATION	W.F.Grand Total	VALIDATION
1988	555,5	1610,26	561,2	1600,05	**563,2**	1601,84
1989	570,1	1629,35	572,8	1615,60	**572,2**	1614,29
1990	579,8	1694,01	586,4	1675,92	**588,1**	1678,17
1991	609,2	1743,92	603,8	1750,81	**604,0**	1753,23
1992	625,9	1767,03	619,3	1812,67	**618,5**	1801,23
1993	634,6	1823,25	625,8	1818,52	**627,1**	1814,49
1994	640,6	1808,52	635,7	1828,87	**637,4**	1853,18
1995	655,1	1895,82	640,1	1898,76	**640,1**	1901,42
1996	687,0	2013,61	711,4	1970,35	**708,2**	1965,37
1997	726,7	2029,82	725,3	2039,04	**724,8**	2034,15
1998	741,9	2119,75	740,8	2125,15	**741,7**	2123,63
1999	743,7	2228,95	748,0	2179,94	**749,6**	2186,96
2000	752,3	2270,24	763,8	2230,18	**766,5**	2232,27
2001	795,0	2363,01	788,6	2390,06	**787,4**	2389,36
2002	803,4	2559,27	797,9	2597,13	**800,4**	2595,94
2003	828,0	2687,46	821,4	2719,82	**818,9**	2719,82
2004	856,0	2791,09	840,1	2812,08	**843,1**	2807,67
2005	895,4	2936,22	890,5	2934,01	**889,9**	2933,24
2006	941,8	3079,57	952,3	3077,28	**950,3**	3079,36
2007	1003,1	3260,55	1015,2	3230,52	**1013,0**	3227,68
2008	1048,5	3594,51	1072,4	3352,76	----------------	3350,88

Table 2 World Fleet prediction results using the regression analysis and ANN

Years	World Seaborne Total Dry Bulk	World Seaborne Total Bulk	World Seaborne Grand Total	World Fleet Total Bulk	World Fleet Grand Total
1985	1460	2859	3631	499	**589**
1986	1416	2859	3628	479	**570**
1987	1334	2703	3625	473	**564**
1988	1409	2925	3893	471	**564**
1989	1592	3283	4162	477	**573**
1990	1599	3209	4156	491	**589**
1991	1625	3200	4192	504	**605**
1992	1597	3262	4337	515	**619**
1993	1616	3424	4545	521	**628**
1994	1673	3498	4650	529	**639**
1995	1782	3648	4867	530	**642**
1996	1815	3780	5111	549	**708**
1997	1908	3971	5422	560	**725**
1998	1897	3960	5440	571	**742**
1999	1894	3999	5561	573	**750**
2000	2037	4213	5904	587	**766**
2001	2094	4323	6019	601	**787**
2002	2168	4378	6203	607	**800**
2003	2288	4639	6547	618	**819**
2004	2465	4931	6948	634	**843**
2005	2561	5113	7255	669	**889**
2006	2699	5302	7611	714	**949**
2007	2787	5385	7852	756	**1011**
2008	2907	5558	8175	789	**1058**
2009	3013	5699	8479	825	**1109**
2010	3126	5846	8787	841	**1142**

Table 3. **World Fleet prediction results 3-DCNN**

Year	**Original**	**Regression**	**ANN**	**3-DCNN**
2004	843.10	856.00	840.10	843.00
2005	889.90	895.40	890.50	889.00
2006	950.30	941.80	952.30	949.00
2007	1013.00	1003.10	1015.20	1011.00
2008		1048.50	1072.40	1058.00
SSqrEr		**19.16**	**4.27**	**2.55**

Table 4 Comparison of results of Regression, ANN and 3-DCNN

MANUFACTURING PARAMETERS		GEOMETRIC PARAMETERS		CAPACITY PARAMETERS	
Parameter	**Value**		**Value Unit**		**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		

Table 5. Input Parameters of the Ships

ANN Vs 3-DCNN		ANN				3-DCNN			
ABSOLUTE PERCENTAGE ERROR		T1 NB212	T2 NB218	T3 NB 220	T4 NB95	T1 NB212	T2 NB218	T3 NB 220	T4 NB95
INDIRECT COSTS	Purchasing & Logistics	1.128	1.795	1.754	1.552	1.005	1.101	0.873	0.745
	Design	1.587	1.915	2.469	1.270	1.211	1.205	1.234	0.873
	Supervision & Production Control	0.374	0.673	0.142	0.475	0.214	0.423	0.076	0.213
	Bookkeeping & Accounting	0.728	0.705	0.398	0.290	0.534	0.437	0.176	0.145
	Maintenance & Administrative	0.463	0.406	0.468	0.472	0.244	0.213	0.254	0.237
	Customer Relationships	1.255	0.515	2.535	0.805	0.765	0.432	1.126	0.403

Table 6. Absolute Percentage Error of ANN and 3-DCNN test results