Design and Development of an Emulated Human Cognition using novel 3D Neural Networks

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ABSTRACT — This paper describes the development of an Emulated Human Cognition (EHC) which is designed and based on a replicated human brain with a right- and a left-hand lobe, one a deductive side and the other a generic one. The emulated human cognition works in a very similar to the human brain. The right-hand lobe consists of a newly designed Artificial Neural Network (ANN) with a multi-hidden layer topology. The right-hand lobe is the deductive side of the EHC and uses logics as well as an integrative method applying iteration to determine a relationship between a set of input values and a set of output values. The left-hand lobe is a newly designed 3-dimensional cellular neural network. The left-hand lobe is the descriptive side of the EHC which uses a generic algorithm for defining the relationship between the adjacent cells (data).

Both lobes use the system equation, one using it in an iterative manner and the other as an integrative. The input variables presented to the EHC are immediately analysed for it to decide which lobe should be activated. Once the decision is made, the appropriate lobe takes the responsibility of computing the data and predicting the desired outcome(s). The EHC, when fully developed, has almost an unlimited memory capacity and is capable of immediate recall of any data in its almost unlimited memory locations. The EHC is capable of parallel processing if each lobe is used simultaneously. The EHC is an aid to any researcher wishing to establish a relationship between any two set of data. EHC has been used in several applications where neural networks have been used to establish relationship between two or more sets of variables. In this paper the EHC has been given two tasks; one to forecast demand for a given product and the other to compute the activity costs of building a new ship. The results have been very promising.

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

I. Introduction

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 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 this Emulated Human Cognition (EHC). The earlier EHC was composed of either an Artificial Neural Network (ANN) or a Cellular Neural Network (CNN). The CNN was later developed into a 3 dimensional network (3-DCNN). 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 emulated human cognition and make references to the multi hidden layer ANN, and the new 3CNN. The EHC is then given the task of predicting the demand for a given type of ship and also to forecast the indirect cost of building the ship. The predicted values and estimated costs of the activities in building a new ship are very good and proof that the EHC is capable of making the right decision and has the capabilities to establish relationships between input and output data with an astonishing degree of accuracy and an acceptable level of reliability.

II. The Main Components of the Emulated Human Cognition

The EHC is technically represented as a system composed of two parallel and distinct sides. One side is deductive and analytical and the other side is generic and descriptive. The deductive side is composed of a novel ANN and the generic side a novel CNN.

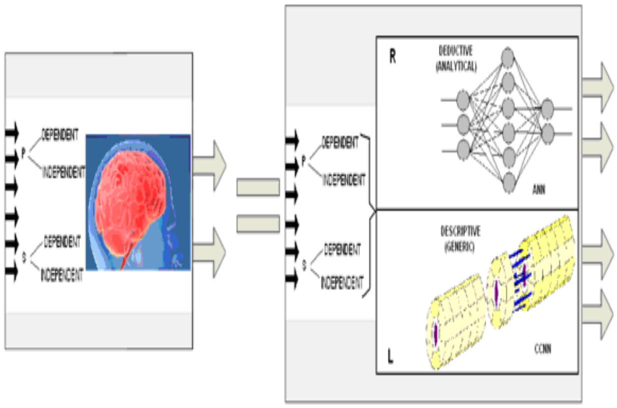


Fig.1. Description of Emulated Human Recognition

All four equations of motion were unified into one single expression and used in the modelling of all components when there is a flow of fluid [13]. Using the same approach as [13] the system theory of $\sum = (U^r, X^n, Y^m, \alpha, \beta)$ was transformed into a family of $\sum_l = (U^r, X^n, Y^m, A, B, C)$ for ANN applications. For CNN applications it was reduced to

$$\frac{dX}{dt} = -X + A * Y + B * U + I \qquad (1)$$

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].

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).

A typical artificial model of a neuron is shown in Fig. 2.

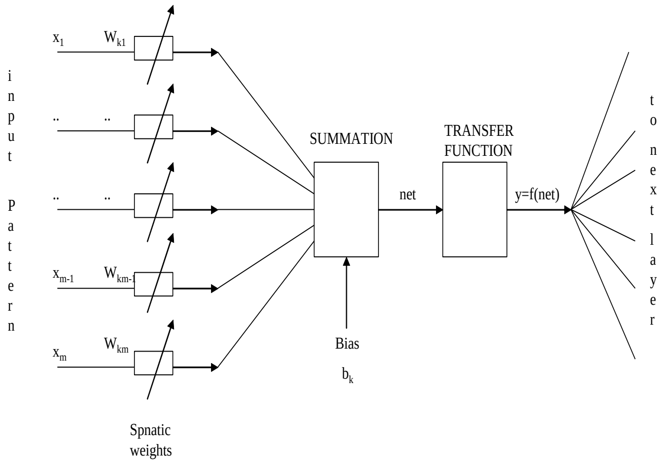
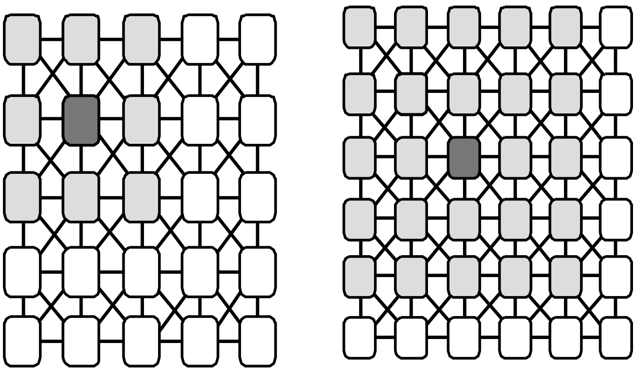


Fig.2. General Block Diagram of a Neuron

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. 3. 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:



r=1 r=2

Fig.3. General Block Diagram of a Neuron

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

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. 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].

III. 3 Dimensional Cellular Neural Networks

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;

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

For the inner cell of the segment n;

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

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.

IV. Training 3DCNN with GA

3DCNN 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.

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

where

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;

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

V. Emulated Human Cognition

To test the EHC, two separate applications were presented to the EHC. The EHC successfully established the relationships for each application. The first application tested to see if the EHC can forecast the Dead Weight Tonne, (DWT) for a particular type of a ship such as 'Bulkers' worldwide, where the EHC decided to use 3DCNN. The second application involved the prediction of the indirect cost for building a particular type of ship; this time the EHC chose the new ANN. The following provides the relevant information about both applications.

1. Application 1-3DCNN

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.

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;

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

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

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

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

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

2. Application 2-ANN with Additional Hidden Layers

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.

Table 1. Original data

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**

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 3.

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.

Table 2. 3DCNN Output Data

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. Input Parameters of the Ships

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		

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].

A. 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.

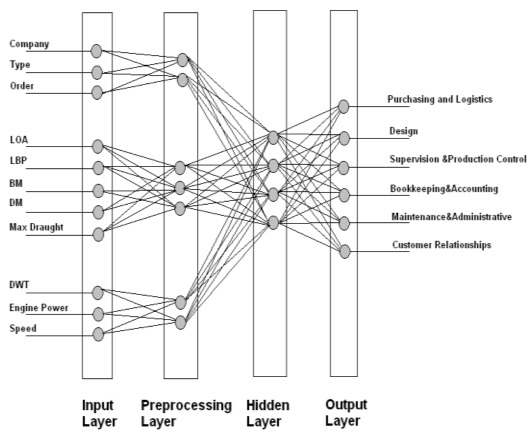


Fig. 4. Neural network structure for predicting the indirect costs

B. Results

The ANN test results for the four ships are shown in Table 4. In this table, ANN test results were compared with the actual Activity Base Costs of the ships, then, the absolute percentage error was calculated.

Table 4. Absolute Percentage Error of ANN test results

ABSOLUTE PERCENTAGE ERROR		T1 NB212	T2 NB218	T3 NB 220	T4 NB95
INDIRECT COSTS	**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

VI. Conclusions

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. This elucidates that the 3DCNN is a good model and as part of the generic (descriptive) lobe of the EHC, it has managed to make the right decision and carry out the millions of iteration to produce output values which are in good agreement with the actual values.

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.

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 4. 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 relationships 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 7 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.

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. Two distinctly different neural networks have been integrated into an emulated human cognition which can now be applied to solve both deductive and generic types of problems where neural network have played a role.

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