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Artificial Neural Network in Marine Traffic Modelling

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Abstract: Infrastructure plays a very important role in the economic progress of a nation. No country can think of economic progress and development without the development of efficient infrastructure. Especially in the age of globalisation where international goods and commodities are to be transported from one country to the other, efficient infrastructure is the key to the success. Taking into consideration 90% of the international cargo is transported through sea ways. The Sethu Samudram ship Canal Project (SSCP) is the mega ongoing infrastructure project of India which provides a continuous navigation route through India's territorial water connecting the east and west coast of India. This will save about 424 nautical miles and about 36 hours of sailing time. SSCP will help to develop the coastal shipping of the all the major and minor ports along the east and west coast of India and improve the international competitiveness of India's EXIM trade. Since the greatest beneficiary of the project is the Tuticorin port, this study investigates the impact of the Sethu Samudram ship channel project on transportation of Tuticorin port, a traffic prediction in terms of Export, import, total tonnage, containers handled and ship handled on the Tuticorin port is carried out in this study by using Artificial Neural Network. As applied in the research Artificial Neural Network analysis assumes that human learning can be emulated by a network of massively interconnected but very simple processing units. The theoretical foundation for the algorithm of the current neural network model is based on Hebb's theory of learning in which connections between pairs of neurons are more strongly reinforced when the neurons are concurrently active. In this study Artificial Neural Network is used to predict the category wise traffic of Tuticorin port, which has the potential to transform into a transhipment hub due to the implementation of Sethu Samudram ship Canal Project.

Key words: SSCP, network, algorithm, ANN, modelling

INTRODUCTION

The Sethu Samudram Ship Canal project envisaging dredging of a ship canal for total length 152.2 km between gulf of manners and Palk Strait. The canal will have a dredged depth of 12 m and bottom width 300 m with side slope 1 in 3 to cater vessels drawing a drought of 10.7 m. The Tuticorin port has the potential to transform in to a international transhipment hub due to the implementation of the project. The ships coming from the west coast of India and other western countries with destination in east coast of India, Bangladesh and China will use the Sethu Samudram ship Canal and Tuticorin port instead of going around Srilankan coast. It is expected that the EXIM trade of the Tuticorin port will get boosted up due to the project. Therefore a traffic prediction for Tuticorin port is carried out by collecting past 96 months traffic data in terms of vessels handled, container handled, import and export handled from Tuticorin port authority. In this study Artificial Neural Network approach is followed for predicting the traffic.

This study will give a clear view about the applications of Artificial Neural Network in Transportation Engineering and this study will be helpful in assessing the impact of Sethu Samudram Ship Canal project on traffic of Tuticorin port and for further studies in Tuticorin Port.

The development of Artificial Neural Network (ANN) began approximately 50 years ago (Mc Culloch and Pitts, 1943) inspired by a desire to understand the human brain and emulate its functioning. Extensive research has been devoted to investigating the potential of Artificial Neural Networks (ANN), as computational tools that acquire, represent and compute a mapping from one multivariate input space to another (Wasserman, 1989). The ability to identify a relationship from given patterns make it possible for ANN to solve large scale complex problems such as pattern recognition, non linear modelling, classification, association and control. Although the idea

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of artificial networks was proposed by Mcculloch and Pitts (1943) over fifty years ago, the development of ANN techniques has experienced a renaissance only in the last decade due to Hopfield's efforts (Hopfield, 1982) in iterative auto associable neural networks.. A tremendous growth in the interest of this computational mechanism has occurred since Rumelhart *et al.* (1986) rediscovered a mathematically rigorous theoretical framework for neural networks i.e., back propagation algorithm. Consequently, ANN have found applications in such diverse areas as neurophysiology, physics, biomedical engineering, electrical engineering, computer science, civil engineering, acoustics, cybernetics, robotics, image processing, financing and others.

Introduction to artificial neural network: An ANN is a massively parallel-distributed information processing system that has certain performance characteristics resembling biological neural networks of human brain (Haykin, 1994). ANN has been developed as a generalisation of mathematical models of human cognition or neural biology. Their development is based on the following rules.

- Information processing occurs at many single elements called nodes, also referred to as units, cells or neurons.
- Signals are passed between nodes through connection links.
- Each connection link has an associated weight that represents its connection strength.
- Each node typically applies a non linear transformation called an activation function to its net input to determine its output signal.

ARTIFICIAL NEURAL NETWORK ARCHITECTURE

A Artificial Neural Network is composed of a set of artificial neurons (nodes) grouped in a number of layers. The first layer and the last layer within a neural network are called input and output layer. The inner layers are known as hidden layers. The information passes from input to the output side. The nodes in one layer are connected to those in the next, but not to those in the same layer. Thus the output of a node in a layer is only a dependent on the input it receives from previous layer and the corresponding weights.

On the other hand, in a recurrent ANN, information flows through the nodes in both direction, from input to the output and vice versa. This is generally achieved by recycling previous network output as current input thus allowing for feedback.

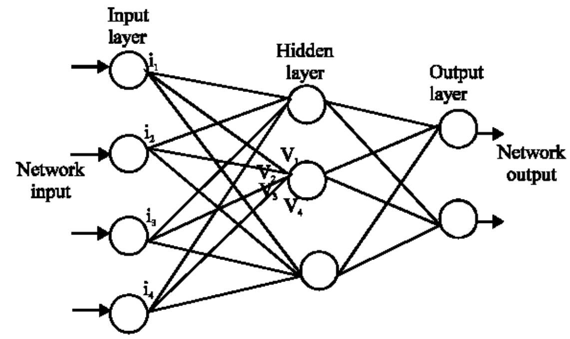

Fig. 1: Configuration of feed forward three-layer ANN

Figure 1 shows the Configuration of a feed forward 3 layer ANN. These kinds of ANN can be used in a wide variety of problem such as storing and recalling data, classifying patterns, performing general mapping from input pattern (space) to output pattern (space), grouping similar pattern or finding solutions to constrained optimization problems.

The node N_i in layer L_n has four properties. These properties are:

- An input vector $I_i = [I_1 \ldots .. i_k]$.
- An output, a_i.
- An activation function, f.
- A training rate μ.

The input vector mimics the signals received by the neuron Ni from all the neurons (k neurons) in the previous layer. To each element of the input vector a weight is associated that makes a weight vector, $V_i = [V_1, \ldots, V_k]$. The weight vector mimics the strengths of synoptic connections between the neuron N_i and the other neurons. The inner product of $I_i\ V_i = S = \Sigma_{ij}\ v_j$ (for $j = 1 \ldots k$) represents the total weighted input (signals) received by node N_i. The activation function f determines the level of excitation for the node N_i. The activation is same for all the nodes of a neural network. The output a_i equals f ($I_i\ V_i$). When the activation function is a sigmoid function then

$$ai = f(s) = \frac{1}{1 + e^{-s}} \quad (1)$$

The training rate is a coefficient ($0<\mu_i<1$) that will be used in training of the node N_i. It may be the same for all the nodes within a neural network.

For the nodes N_i, …., N_j in layer $L_{,n}$ the weight vectors ofV_i, …, V_j related to input vectors of I_1, ….I_j make a matrix of J columns and k rows, W_n. The output for the layer L_n is a vector $A_n=[a_1, \ldots a_j]$ and it is calculated as.

$$A_n = f(I_n\text{-}W_n) \quad (2)$$

Because all nodes in the layer L_n have the same input vectors, then $I_x = I_i$ (although the input vectors for all the nodes of layer L_n are the same but their associated weight vectors are not). If the neural network is composed of $L_1,\ldots, L_m$ layers, then the output for each layer is calculated according to Wasserman (1989). The output of layer L_i is fed as input to the next layer L_{i+1}. This process continues until the final output vector is produced. The process of taking an input and sending it through all the layers of a neural network to generate the final output vector is referred to as a forward pass.

Neural network training: Using a training paradigm, a neural network may be trained to generate the desired output vector, for individual input vector of a training data set. The training paradigm of interest is the back – propagation algorithm. For a given input vector, it generates the output vector by a forward pass. Then the difference between the output vector and the desired output vector is back propagated through the neural network (from the output layers to input layers) to modify the weight matrices for the entire neural network. This process is referred to as a reverse pass. The algorithm was originally developed by Werbos. It has been rediscovered by Rumelhart *et al.* (1986) and made it popular in demonstrating how to train the hidden neurons for a complex mapping problem.

In the reverse pass, the training of the neural network takes place. Training the network means that all the weights in the weight matrices will be modified based on Δ rules (Gross Berg, 1974). For example, the weight V_j associated with input i_j for the node N_j in the output layer is changing to a new weight V'_j as

$$V_j = V_j + \Delta_j \quad (3)$$

The value of Δ_j is calculated using

$$\Delta_j = \mu_j \,.\, \delta_j i_j \quad (4)$$

Where, μ_j is the training rate for the node N_j and δ_j is calculated as

$$\delta_j = \frac{\partial f(S_j)}{\partial S_j}(t_j - a_j) = a_j(1-a_j)(t_j - a_j) \quad (5)$$

In which f is the activation function, S is the sum of weighted input, a_j is the output, t_j is the desired out for node N_j and i_j is an input to the node N_j and the weight associated to this input will be modified.

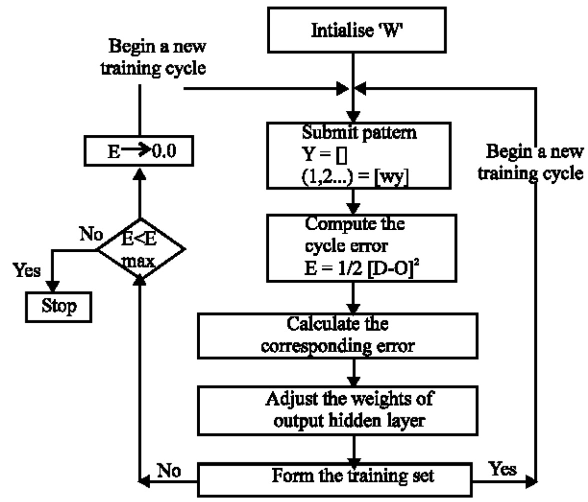

Fig. 2: Configuration of back propagation Network

When δ_j is less than or equal to a tolerance level, then node N_j has learned the input pattern. The weight matrices related to the input vectors of the nodes in the hidden layers are also modified according to the Eq. 3 and 4. Because a desired output is not known for a given node in an inner layer, then δ for the node is calculated differently as follows.

Let M_k be a node in an inner layer (the layer immediately before the output layer). Let the output of M_k be a_{mk}, which is fed as input to all the h nodes of the output layer. Let the weight associated with these h inputs makes the weight vectors of $G = (g_1, g_h)$. Let the δ_s calculated for h nodes of the output layer make the vector $D = [\delta_1,\ldots, \delta_h]$. The inner product of G and D is

$$G.D = \alpha = \sum_{i=-1}^{h} g_i \delta_i \quad (6)$$

and

$$\delta_{mk} - a_{mk}(1 - a_{mk})\,\alpha \quad (7)$$

As shown above the δ_s for the nodes in inner layer L_j are calculated based on the δ_s for the nodes in layer L_{j+1}

After a neural network is trained, it is tested against the records, of a testing data set that have not been previously encountered by the network. For these records, the desired output is known. The out put generated for each record of this testing data is checked against the desired output for that record. If there is a match, then it is concluded that the trained neural network could recognise the record correctly.

Figure 2 shows the flow chat of back propagation network.

Strengths and limitation: The following are some of the reasons ANN have become an attractive computational tool:

- They are able to recognize the relation between the input and output variable without explicit physical consideration.
- They work well even when the training sets contain measurement errors.
- They are able to adopt solutions over time to compensate for changing circumstances.
- They possess other inherent information-processing characteristics and once trained are easy to use.

Although several studies indicate that ANN have proven to be potentially useful tool in to Transportation, their disadvantages should not be ignored. The success of an ANN application depends both on the quality and the quantity of data available. One of the major limitation of ANN is the lack of physical concepts and relations. This has been one of the primary reasons for the sceptical attitude towards this methodology. The fact that there is no standardized way of selecting network architecture also receives criticism. The choice of network architecture, training algorithm and definition of error are usually determined by the user's past experience and preference rather than the physical aspect of the problem.

APPLICATION OF ARTIFICIAL NEURAL NETWORK IN TRANSPORTATION

Artificial Intelligence (AI) techniques are suitable for application to specific transportation problems that are amenable to treatment on the basis of rules and relationships (Taylor, 1990). Further, these problems may be considered on the basis of incomplete or even conflicting information. In particular, there should be many possibilities for using AI in the planning and operation of transportation systems to enhance decision making.

There are several reviews of potential application of AI to transportation planning and engineering, including Tak allou, Bonsall, Ritchie and Szwed.

This research to evaluate the performance of a neural network in predicting the total traffic on Tuticorin port represents an initial application of an A.I, technique in marine traffic. If a neural network can successfully predict the total traffic in Tuticorin port, then A.I techniques can play an important role in the traffic movement of water ways.

Traffic data set: The data set for thus research is comprised of past 96 months traffic handled in Tuticorin port of India. Each record set is categorical data of total import, total export, total traffic, total container handled, number of ships handled and total tonnage handled, in the Tuticorin port. There are 60 records in the training set as in put, 24 records in the testing set for validation and 12 month records are used for prediction and comparison. Tables provide the descriptive statistics of traffic handled and predicted in Tuticorin port.

MODEL VALIDATION

The performance of a trained ANN can be fairly evaluated by subjecting it to new patterns that it has not seen during training. The performance of the network can be determined by computing the percentage errors between predicted and measured values. Since finding optimal network parameters is essentially a minimization process, it is advisable to repeat the training and validation processes several times to ensure that satisfactory results have been obtained. Table 1-4 represent the percentage error of measured and predicted values of total export, import, container and ship handled in Tutucorin port.

Table 1: Predicted export

	Total exports in tonnes			
Month	Measured	Predicted	Variation	%Error
85	299464	298794.89	669.11	0.22
86	361273	371476.30	-10203.30	-2.82
87	376504	364506.40	11997.60	3.19
88	306721	291394.77	15326.23	5.00
89	366678	355371.38	11306.62	3.08
90	411502	403332.85	8169.15	1.99
91	433683	426334.07	7348.93	1.69
92	389592	379452.30	10139.70	2.60
93	330356	335408.00	-5052.00	-1.53
94	329438	329042.02	395.98	0.12
95	341418	345159.56	-3741.56	-1.10
96	344405	359203.04	-14798.04	-4.30

Table 2: Predicted import

	Total import in tonnes			
Month	Measured	Predicted	Variation	%Error
85	1186368	1137684.64	48683	4.10
86	880154	954162.57	-74009	-8.41
87	980157	973156.56	7000.4	0.71
88	805249	813144.11	-7895.1	-0.98
89	998351	968160.55	30190	3.02
90	1004976	1137684.64	-8543.2	-0.85
91	1107439	1122472.31	-15033	-1.36
92	1196111	1157891.47	38220	3.20
93	1152138	1140309.32	11829	1.03
94	1150086	1157159.25	-7073.3	-0.62
95	1462316	1264793.12	197523	13.51
96	1274380	1257899.52	16480	1.29

Table 3: Predicted TEUS

Month	Total containers in teus Measured	Predicted	Variation	%Error
85	25841	25926.82	-85.82	-0.33
86	25614	24354.43	1259.57	4.92
87	32632	30109.12	2522.88	7.73
88	26676	25109.12	1566.88	5.87
89	26833	26024.53	808.47	3.01
90	29565	28380.40	1184.60	4.01
91	33795	32208.92	1586.08	4.69
92	36215	35208.92	1006.08	2.78
93	31184	30099.21	1084.79	3.48
94	28762	27973.06	788.94	2.74
95	26716	26203.80	512.20	1.92
96	32060	31109.12	950.88	2.97

Table 4: Predicted ships

Month	Total ships in numbers Measured	Predicted	Variation	%Error
85	134	126	7.48	5.58
86	121	127	-6.7	-5.54
87	135	128	6.51	4.82
88	101	104	-3.39	-3.36
89	122	120	1.49	1.22
90	131	118	12.55	9.58
91	132	125	6.71	5.08
92	142	125	16.71	11.77
93	128	123	4.28	3.34
94	120	119	0.43	0.36
95	129	123.32	5.68	4.40
96	130	126.02	3.98	3.06

CONCLUSION

This study serves as an introduction to Artificial Neural Network (ANN) with emphasis on their application in Transportation Engineering. It presents a brief description of ANN, the under laying concept and Mathematical aspects and the role of ANN relative to other modelling approaches in Transportation. Some popular ANN architecture and algorithms are discussed. The merits and short coming of this methodology are discussed. The artificial neural network in this study has demonstrated its usefulness and accuracy in predicting the traffic of Tuticorin port, which is going to gets maximum benefits due to the implementation of Sethu Samudram Ship Canal, Project. The variation between the measured values and predicted values of Traffic is very less this proves that the artificial neural network has correctly predicted the traffic of Tuticorin port. It is expected that there will be fourty percentage growth in traffic in addition to the traffic predicted in Tuticorin port due to the implementation of Sethu Samudram Ship Canal Project. Further studies are required in future to asses the impact of this project on traffic of Tuticorin port.

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