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Original Research Paper

Impact of Sethu Samudram Ship Canal Project on Marine Traffic - An Artificial Neural Network Modelling

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ABSTRACT

This paper 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 underlaying concept and mathematical aspects and the role of ANN relative to other modelling approaches in transportation. Some popular ANN architecture and algorithms, and the merits and shortcomings of this methodology are discussed. The artificial neural network in this paper 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, thus, proving that the artificial neural network has correctly predicted the traffic of Tuticorin port.

INTRODUCTION

India is surrounded by Bay of Bengal, Arabian Sea and Indian Ocean on three sides having a peninsular coast of 7517 kilometres studded with 12 major ports and 185 intermediary and minor ports. Shipping trade between the east and west coast of India has been prevailing for a long time. Yet, India does not have a continuous navigable channel with its territorial waters connecting the east and west coasts. Currently, the ships coming from the west coast of India and other western countries with destination in east coast of India, Bangladesh and China, etc. have to navigate around Srilankan coast. The existing waterway is shallow and not sufficient for the movement of ships. This is due to presence of a shallow reef at Adam bridge near Pampan island, where the navigable depth is about 3 m only. Proposal for dredging, a ship canal between Gulf of manner and Palk Strait through Adam bridge has been envisaged so that the ships plying between the east coast to west coast of India need not go around Srilanka. Sethu Samudram Ship Canal Project (SSCP), which envisages dredging of a ship canal between Gulf of Mannar and Palk Strait has been approved by Government of India in September 2004 and the dredging work is in progress. Since the greatest beneficiary port due to the implementation of the Sethu canal project is Tuticorin port, a detailed traffic study and traffic prediction for Tuticorin port is carried out in this paper 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 (Hebb 1949) of learning in which connections between pairs of neurons are more strongly reinforced when the neurons are concurrently active.

In this paper artificial neural network is used to predict the categorywise traffic of Tuticorin port, which has the potential to transform into a transshipment hub due to implementation of Sethu

Samudram Ship Canal Project. This study will give a clear view about the applications of artificial neural network in transportation engineering, which will be helpful for further studies in Tuticorin port. The objectives of Sethu Samudram Canal Project are:

- SSCP has the objective of creating a navigation channel from the Indian Ocean to the Bay of Bengal through Gulf of Manner, Adam Bridge, Palk Bay and Palk Strait within Indian territorial waters.
- To provide a continuous navigable short cut route for ships going from west coast of India to the east coast and vice versa.
- It aims at creation of a two-way navigable channel of 12 m deep and 300 m width by dredging the sea bed at Adam bridge and some stretches of Palk Bay and Palk Strait.

PROPOSED ROUTE OF SETHU CANAL

The proposed SSCP project will have a dredged depth of maximum 12m and a bed width of 300m providing a two-way channel for vessels drawing a draught of 10.7m. A side slope of 1 in 3 is to be provided.

The Sethu ship canal route will originate from the Tuticorin port in Gulf of Manner utilizing the available depth of about 20m up to Coast of Pampan island passing through a canal to be dredged up to maximum 12m in the Adam bridge, proceeding parallel to international medial line, in the Palk bay and further through a canal to be dredged 12m depth in the Palk Strait terminating in the Bay of Bengal as shown in the Fig. 1. The Sethu Samudram ship channel will reduce sailing distance of about 444 nautical mile between Tuticorin and Chennai and about 300 nautical miles between Tuticorin and Visakhapatnam as shown in Table 1.

BACKGROUND ON NEURAL NETWORK

The development of Artificial Neural Network (ANN) began approximately 50 years ago inspired by a desire to understand the human brain and emulate its functioning. Extensive research has been carried out to investigate the potential of 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, nonlinear modelling, classification, association, and control. Although the idea of artificial networks was proposed about 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 mecha-

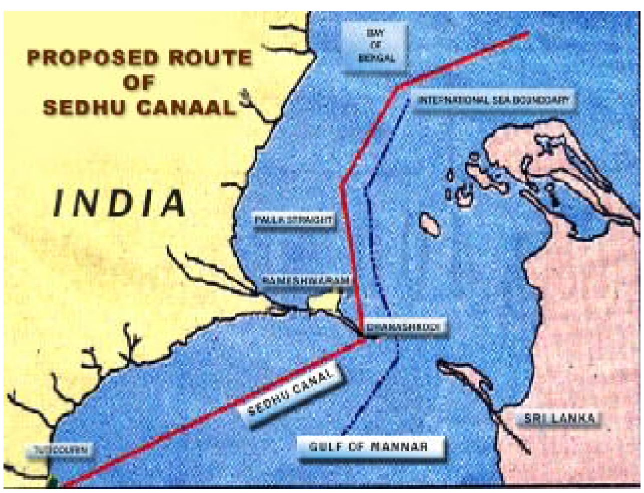

Fig. 1: Proposed route of Sethu canal.

Table 1: Savings in mileage and voyage time.

From	To	Existing route around Srilanka	Through Sethu Canal	Saving in miles	Travel time reduced
Tuticorin	Chennai	769	335	424	25 to 35 hours
Tuticorin	Vishakapatnam	1028	652	366	
Tuticorin	Calcutta	1371	1031	340	

**All distance are in nautical miles

nism has occurred since Rumelhart rediscovered a mathematically rigorous theoretical framework for neural networks, i.e., back propagation algorithm. Consequently, ANN have found application in such diverse areas like 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 have been developed as a generalisation of mathematical models of human cognition or neural biology. Their development is based on the following rules.

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

ARTIFICIAL NEURAL NETWORK ARCHITECTURE

An ANN 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 dependent only 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 directions, from input to output and vice versa. This is generally achieved by recycling previous network output as current input, thus, allowing for feedback.

Fig. 2 shows the configuration of a feed forward three layer ANN. These kinds of ANN can be used in a wide variety of problems 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.

1. an input vector $I_i = (I_1.....i_k)$
2. an output, a_i
3. an activation function, f
4. a training rate, μ

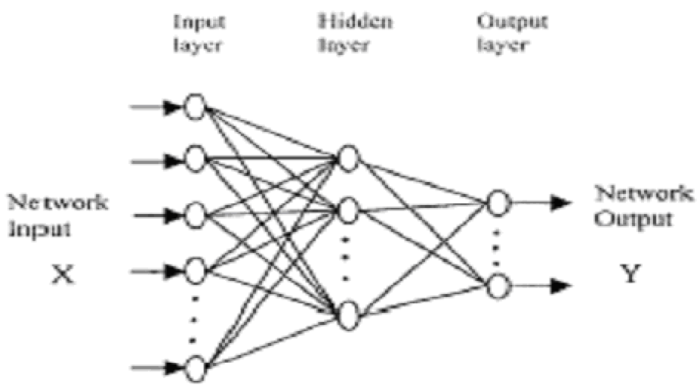

Fig. 2: Configuration of feed forward three-layer ANN.

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 $I_i\,V_i = S = S_{ij}\,v_j$ *(for j=1, …, 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,

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

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 $N_i, \ldots, N_j$ in layer L_n, the weight vectors of $V_i, \ldots, V_j$ related to input vectors of $I_1, \ldots I_j$ 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 calculated as,

$$A_n = f\,(I_n - W_n) \qquad ...(2)$$

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.

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. 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

$$V_j = V_j + \Delta_j \qquad ...(3)$$

The value of D_j is calculated using

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

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

$$d_j = \frac{\partial f(S_j)}{\partial S_j}(t_j - a_j) = a_j(1 - a_j)(t_j - a_j) \qquad ...(5)$$

in which f is the activation function, S is the sum of weighted input, a_j is the output, t_j is the desired output 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. 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 equations (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 $G = (g_1, \ldots, g_h)$. 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

$$G.D = a = \sum_{i=-1}^{h} g_i d_i \qquad ...(6)$$

and

$$\delta_{mk} - a_{mk}\,(1 - a_{mk})\,a \qquad ...(7)$$

As shown above the δ_s for the nodes in inner layer L_j are calculated based on 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 output 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 recognize the record correctly. Fig. 3 shows the flow chart of back propagation network.

STRENGTHS AND LIMITATION OF ANN

Following are some of the reasons ANN have become an attractive computational tool.

1. They are able to recognize the relation between the input and output variable without explicit physical consideration.
2. They work well even when the training sets contain measurement errors.
3. They are able to adopt solutions over time to compensate for changing circumstances.
4. 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 limitations of ANN is the lack of physical concepts and relations. This has been one of the primary reasons for the skeptical 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.

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 technique can play an important role in the traffic movement of waterways.

Traffic data set: The data set for this research is comprised of past 96 months traffic handled in Tuticorin port. Each record set is categorical data of total import, total export, total traffic, total containers handled, number of ships handled, and total tonnage handled in the Tuticorin port. There are 60 records in the training set as input, 24 records in the testing set for validation, and 12 month records used for prediction and comparison. Tables 2-5 provide descriptive statistics of traffic handled and predicted in Tuticorin port.

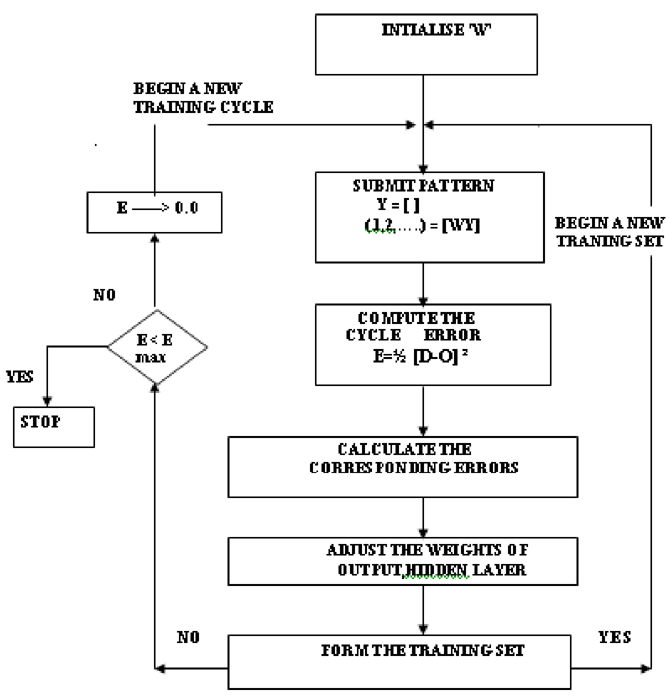

Fig. 3: Configuration of back propagation network.

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. Tables 2-5 represent the percentage error of measured and predicted

Table 2: Predicted export.

		Total exports in tonnes		
Month	Measured	Predicted	Variation	% Error
85	299464	298794.89	8691.11	0.22
86	361273	371476.3	-10203.3	-2.82
87	376604	364506.4	11997.6	3.19
88	306721	291394.77	15326.23	5.00
89	368678	356371.38	11306.62	3.08
90	411502	403332.85	8169.15	1.99
91	433683	426334.07	7348.93	1.69
92	389692	379452.3	10139.7	2.60
93	330356	335408	-5062	-1.53
94	329438	325042.02	395.58	0.12
95	341418	345159.56	-3741.56	-1.10
96	344405	359203.04	-14758.04	-4.30

Table 3: Predicted TEUS.

		Total containers in TEUS		
Month	Measured	Predicted	Variation	% Error
85	25841	25926.82	-8582	-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	29585	38380.4	1184.6	4.01
91	33796	32208.92	1586.08	4.68
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	26715	26203.8	512.2	1.92
96	32080	31109.12	950.88	2.97

Table 4: Predicted import.

		Total imports in tonnes		
Month	Measured	Predicted	Variation	% Error
85	1186368	1137684.64	4868.3	4.10
86	880154	954162.57	-74009	-8.41
87	980157	973156.56	7000.4	0.71
88	805249	813144.11	-7896.1	-0.98
89	998351	988160.55	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	1254793.12	197523	13.51
96	1274380	1257899.52	16480	1.29

Table 5: Predicted ships.

		Total ships in numbers		
Month	Measured	Predicted	Variation	% Error
85	134	136	7.48	5.58
86	121	127	-6.7	-5.54
87	135	128	6.51	4.82
88	101	104	-3.38	-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

values of total export, import, container and ship handled in Tuticorin port.

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