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# FORECASTING THE SUEZ CANAL TRAFFIC: A NEURAL NETWORK ANALYSIS

## Key Words

***Maritime Traffic; Suez Canal; ARIMA Models; Neural Nets; Forecasting.***

## Abstract

*Although the Suez Canal is the most important man-made waterway in the world, rivaled perhaps only by the Panama Canal, little research has been done into forecasting its traffic flows. This paper uses both univariate ARIMA and Neural network models to forecast the maritime traffic flows in the Suez Canal which are expressed in tons. One of the important strengths of the ARIMA modeling approach is the ability to go beyond the basic univariate model by considering interventions, calendar variations, outliers, or other real aspects of typically observed time series. On the other hand, neural nets have received a great deal of attention over the past few years. They are being used in the areas of prediction and classification, areas where regression models and other related statistical techniques have traditionally been used. The models obtained in this paper provide useful insight into the behavior of maritime traffic flows since the reopening of the Canal in 1975- following an 8 year closure during he Arab-Israeli wars (1967-1973)- till 1998. The paper also compares the performance of ARIMA models with those of neural networks on an example of a large monthly dataset.*

## Introduction

The 195 km-long Suez Canal is considered the world's longest non-locks waterway. The system extends from Port Said in the North to Port Tawfiq/ Suez in the South. When it opened, the Canal had a draft of 26 feet. Since then, it has been widened and deepened a number of times and by 1996 ships with draft up to 58 feet were able to transit the Canal both

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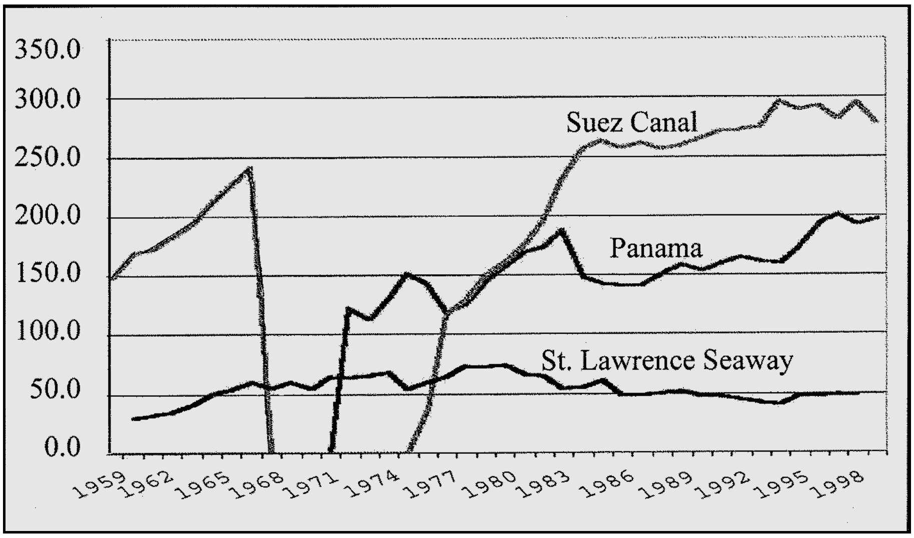
**Figure 1**
**World Major Canals Historical Traffic, 1959-1998 (Mt)**




ways. Historically, the Canal was closed five times to navigation; the most recent closure was for 8 consecutive years from 1967 to 1975 following the Egyptian- Israeli military conflict. The system was reopened to navigation in June 1975.

The Suez Canal is the most important man - made waterway in the world, rivaled perhaps only by the Panama Canal (See Figure 1). The Canal has a strategic location. It links two oceans and two seas: the Atlantic and the Mediterranean via Gibraltar to Port Said, and the Indian Ocean and the Red Sea via Bab Al Mandab.

The Suez Canal is also of utmost importance to both Egyptian economy and world trade. Income from the toll charges imposed by the Suez Canal Authority (SCA) amount to nearly $2 billion per annum and such an income provides the major source of revenue, after tourism (CBE, 2000). The Suez Canal's importance for world trade lies in both its commercial and strategic benefits, with savings in distance, time and transport cost (Gribbin, 1975). For example, The distance between Jeddah (Saudi Arabia) and the port of Constanza (Black Sea) is 11771 miles via the Cape of Good Hope, while it is only 1698 mile via the Suez canal, thus a saving of 86% in distance is achieved. A saving of 23% in distance is also achieved by using the Suez Canal for the trip from Rotterdam in Holland to Tokyo if compared with the route round the African coast. (see Table 1).

**Table 1**
**Some Voyage Distances from Persian Gulf to Major Oil Markets Via Suez and Cape of Good Hope (in Nautical Miles)**

| Route | Via Cape | Via Suez | Saving |
|---|---|---|---|
| Mina Al Ahmadi to Rotterdam | 11294 | 6591 | 4703 (41%) |
| Mina Al Ahmadi to Fos | 10897 | 4804 | 6093 (56%) |
| Mina Al Ahmadi to New York | 11938 | 8429 | 3509 (29%) |

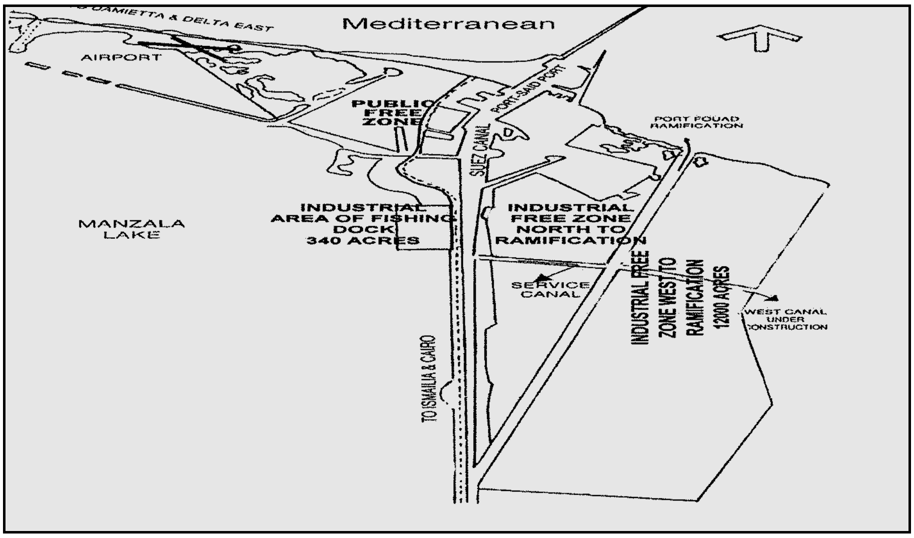
Source: SCA (2000), Annual Statistics.

In a typical year some 20000 vessels may use the Canal and about 35% of the tonnage passing through the waterway belongs to oil trade (Griffiths, 1995). For now, 14 per cent of total world trade, 26 per cent of oil exports and 41 per cent of the total volume of goods and cargo that reach Arab Gulf ports go through the Canal. The average time for negotiating the Canal is 16 hours for the south - bound convoy and 11 hours for the convoys traveling in the opposite direction (Ibrahim, 1999).

(Please refer to Figure 2 for a Suez Canal map).

Against such a background, it is crucial to forecast the volumes of maritime traffic flow through the Canal expressed in tons. Forecasting maritime traffic flows has witnessed an increased interest recently (Dagenais and Maritn, 1987; Gooijer and Klein 1989; Klein and Verbeke, 1987).

**Figure 2**
**Suez Canal Map**



Because of the influence of stochastic elements (e. g. route competition, changes in global economy, like the East Asian financial crisis, etc ...) on traffic flow time series, it is necessary to use a method which is able to filter such undesired elements. One method with such filtering abilities is the ARIMA method. The virtue of ARIMA is well charcterised by Vandaele (1983): ".... can be viewed as an approach by which time series data are sifted through a series of progressively finer sieves". The aim of sifting some components is to identify so- called' white noise processes' (merely stochastic influences on the time series). Another approach with such capabilities is neural network (NN) models. These models consist of many simple elements (units, neurons or nodes, processing elements) which are interconnected. Their way of working can be described as the parallel interaction of these simple elements where several operations are performed at the same time. NN are not programmed but trained with a large amount of examples and they do not store their information locally but all units are responsible for working correctly. This results in a major advantage since the loss of some elements or incomplete input does not automatically lead to an inaccurate forecast (Schumann, 1993).

## Research Objectives

Suez Canal is one of the world's important waterways, For Egypt, it is one of the country's largest foreign currency earners. Despite this fact, little research has been done into forecasting its traffic flows. This paper attempts to fill this gap through forecasting the maritime traffic flows in the Suez Canal in order to help the Suez Canal Authority (SCA) plan its future activities given the unusual fluctuations in regional and international politics.

In recent years, neural networks have become popular in the scientific and business fields. In the transport industry, researchers have recently devoted attention to the application of neural networks to the classification of travel behavior. However, no previous attempt has been made to compare the performance of neural networks with those of traditional forecasting techniques within the field of maritime transport.

Some researchers believe neural networks can capture more complex relationships between and among variables than can traditional statistical analysis (Zurada *et al.*, 1999). However, not all prior research supports the superiority of neural networks over traditional statistical techniques. For example, in a study of healthy and financially vulnerable or unsound Italian industrial firms, Altman *et al*., (1994) found that a neural network produced classification results comparable and sometimes superior to linear multiple discriminant analysis (LDA). However, they concluded that LDA produced better results overall because of concern about the neural network producing illogical weightings of some indicators and overfitting in the training stage.

One of this research objectives is to compare the performance of both ARIMA and neural network models using the same data set.

## Literature Review

In recent years, Neural Networks (NN) have become extremely popular for prediction and forecasting in a number of areas, including finance, power generation, medicine, water resources and environmental science. Although the concept of artificial neurons was first introduced in 1943 (McCulloch and Pitts, 1943), research into applications of NN has blossomed since the introduction of the back propagation training algorithm for feedforward NN in 1986 (Rumelhart *et al*., 1986). NN may thus be considered a fairly new tool in the field of prediction and forecasting.

One of the first successful applications of NN in forecasting is reported by Lapedes and Farber, 1988. Using two deterministic chaotic time series generated by the logistic map and the Glass- Mackey equation, they designed the feedforward neural networks that can accurately mimic and predict such dynamic nonlinear systems.

There is an extensive literature in financial forecasting applications of NN (e. g. Desai and Bharati, 1998; Salchenberger *et al*., 1992; Franses and Van Homelen, 1998; Wikowska, 1995; Coats and Fant, 1993; El Shazly and El Shazly, 1999; Harvey *et al*., 2000).

Another major application of neural network forecasting is in electric load consumption (e. g. Darbellay and Slama, 2000; McMenamin and Monforte, 1998; Kiartzis *et al*., 1995; Ricardo *et al*., 1995).

Many other forecasting problems have been solved by NN. A short list includes commodity prices (Kohzadi *et al*., 1996), environmental temperature (Balestrino *et al*., 1994), airline passenger traffic (Nam and Yi., 1997), ozone level (Ruiz - Suarez *et al*., 1995), student grade point averages (Gorr *et al*., 1994), total industrial production (Aiken *et al*., 1995), futures trading (Kaastra and Boyd, 1995), temperature profiles in oil wells (Farshad *et al*., 2000), inflation (Aiken, 1999), room occupancy (Law, 1998), advertising (Poh *et al*., 1998), cost flow (Boussabaine and Kaka, 1998), political risk (Al- Tabtabai, 2000), insurer insolvency (Brockett and Cooper, 1994); length of stay in hospitals (Pofahl and Walczak, 1998), auditing (Green and Choi, 1997) and market trends (Aiken and Bsat, 1999).

The field of transport studies has also seen an explosion of interest in neural network in the 1990s (Dougherty, 1995) This can be also seen as part of a general pattern of increased use of artificial intelligence techniques in transport (Kirby and Parker, 1994); Despite this fact there is quite a few applications of neural networks in maritime transport. A study by Stamenkovich, 1991, has shown that neural nets have potential for use in autonomous ship navigation in confined spaces. An unusual aspect of this work is that the neural network was used as a supervisor for a more conventional control model, rather than to control the ship directly. A second paper concerns the use of learning vector quantisation networks in an image processing system which recognises and classifies profile images of ships (Lo and Bavarian, 1991). Whilst this particular piece of work is probably of little civilian interest, it nevertheless points to possible future applications of neural networks in maritime industry. Vukadinovic *et al*, 1997, used a neural network approach to the vessel dispatching problem. This paper has shown that the proposed neural network can be used to emulate the dispatcher's decision making process. Training of the proposed neural network involves use of a data base of collected dispatchers decisions that are values for the inputs and outputs of the neural network. The paper also has shown that trained network needs a very short time to solve any given problem, so it can be used in real time

Our paper uses a neural network approach to forecasting the Suez Canal traffic. The forecasting of traffic falls into two distinct categories (Dougherty, 1995): Strategic forecasting is where an attempt is made to predict traffic flows months or years into the future, and usually influences major decisions on planning. Our paper falls in this category. In contrast, short - term forecasts often have a horizon of only a few minutes, and can conceivably feed directly into traffic control systems. Neural networks have been used in both strategic (Chin *et al.*, 1992) and short - term (Dougherty *et al.*, 1994, Dougherty and Cobbet, 1994; Clark *et al.*, 1993) forecasts. Promising results are reported in both cases. The latter paper has a particularly interesting theme in that it makes a considerable effort to compare the neural networks against ARIMA time - series modeling.

## Research Design

### Data

Monthly net ton data is obtained from the Suez Canal Authority (SCA).Data is composed of monthly traffic through the Canal expressed in thousands of tons from reopening of the Canal in June 1975 through June 1998.

### Experimental Design

The number of input nodes is perhaps the most important factor in neural network analysis of a time series since it corresponds to the number of past lagged observations related to future values. It also plays a role in determining the autocorrelation structure of a time series.

The number of hidden nodes allows neural networks to capture nonlinear patterns and detect complex relationships in the data. Without hidden nodes, simple perceptrons are equivalent to linear statistical models. In general, networks with too few hidden nodes may not have enough power to model and learn the data. But networks with too many hidden nodes may cause overfitting problems, leading to poor forecasting ability. Ten levels of the number of input nodes ranging from 1 to 10 will be used in this study. For a linear time series problem, previous research shows that the most common order of autoregressive terms is 1 or 2 and very few problems have order 3 or more (Pankratz, 1983). For nonlinear time series, there are no reports on the number of autoregressive terms typically used for real life applications. We experiment with a relatively large number of input nodes. There is no upper limit of hidden nodes in theory. However, it is rarely seen in the literature that the number of hidden nodes is more than double the number of input nodes (Zhang *et al*., 1998). In addition, previous research indicates that the forecasting performance of neural networks is not as sensitive to the number of hidden nodes as it is to the number of input nodes (Lachtermacher and Fuller, 1995). In this study we will experiment with fifteen levels of hidden nodes from 1 to 15. the combination of ten input nodes and 15 hidden nodes yields a total of 150 neural network architectures being considered for each in - sample training data set.

Sample size is another factor which can affect the forecasting ability of neural networks. In the neural network literature, large samples are often claimed to be beneficial in training neural network models due to the large set of parameters involved in a neural network. However, Kang (1991) in a comprehensive study of neural network time series forecasting, finds the neural network models do not necessarily require a large set to perform well. This study uses a data set comprised of 277 data points.

We will focus on one -step-ahead forecasts as in Diebold and Nason, 1990. One -step-ahead predictions are useful in evaluating the adaptability and robustness of a forecasting method. In one - step - ahead forecasting, the traffic values are forecasted one step at a time and the actual rather than the forecasted values are then used for the next prediction in a forecasting horizon.

One poor prediction will not have serious consequences in a one-step-ahead forecasting system since the actual value will be used to correct itself for the future forecasts. Furthermore, the random walk model will be used as a benchmark for comparison. The random walk is a one-step-ahead forecasting model since it uses the current observation to predict the next one. It is easy to see that random walk models will produce forecasts in one-step-ahead than in multiple-step-ahead forecasts which rely on one single observation as predictions for all future values in a time horizon.

A three-layer feedforward neural network is used to forecast the suez Canal traffic. Sigmoid activation function is employed in the hidden layer and the linear activation function is utilized in the output layer. Given that we are interested in one-step-ahead forecasts, one output node is deployed in the output layer. We use node biases only in the output nodes, based on the proof in Cybenko, 1989, and Hornik *et al.*, 1989, that for neural networks to be universal function approximates, it is not necessary to have hidden node biases. Moreover, without hidden node biases, a more parsimonious model is achieved since fewer model parameters (weights) have to be estimated. Parsimony is a critical model characteristic for a forecasting situation where generalization of past patterns into the future is of utmost importance. It has been found that neural networks without hidden node biases often predict more accurately than those with hidden node biases (Hu *et al.*, 1996). Table (2) compares the performance of the neural network with and without hidden node biases.

There is no consensus on whether data normalization should be used (Zhang *et al.*, 1998). For example, it is still unclear whether there is a need to normalize the inputs because the arc weights can undo the scaling. Shanker *et al.*, 1996, investigated the effectiveness of linear and statistical normalization methods for classification problems. They found that the data normalization does not necessarily lead to better performance particularly when the network and the sample size are large. Hence, raw data are used in this study.

**Table 2**
**Experimentation with and without Hidden Node Biases**

| Number of Neurons | RMSE for NN with hidden node biases | RMSE for NN without hidden node biases |
|---|---|---|
| 1 | 2373.69 | 2029.64 |
| 2 | 2231.92 | 1965.53 |
| 3 | 2018.51 | 1947.77 |
| 4 | 1990.81 | 1931.81 |
| 5 | 1985.39 | 1945.36 |
| 6 | 2012.79 | 1931.22 |
| 7 | 1973.05 | 1880.05 |
| 8 | 1977.57 | 1902.62 |
| 9 | 1977.57 | 1890.28 |
| 10 | 1965.53 | 1929.41 |
| 11 | 1968.24 | 1943.26 |
| 12 | 1971.55 | 1934.53 |
| 13 | 1970.04 | 1934.95 |
| 14 | 1964.02 | 1945.06 |
| 15 | 1969.14 | 1937.84 |

## Performance Measures and Comparison

There is no consensus on the most appropriate measure to assess the performance of a forecasting technique. Here, we use the most popular criterion: RMSE (Root Mean Square Error) to evaluate the predictive performance of neural networks. This forecasting accuracy measure is as follows:

$$\text{RMSE} = \sqrt{\frac{\sum(Y_t - \hat{Y}_t)^2}{N}}$$

Where $y_t$ is the actual observation, $\hat{Y}_t$ is the predicted value, and N is the number of observations. This criterion is mean based and is frequently used performance measure in the literature (Rzempoluck, 1998).

We also apply the traditional Box-Jenkins ARIMA models to the traffic data. The Box-Jenkins models will be implemented with the Forecast Pro statistical system (Forecast Pro, 2000). Forecast Pro is a statistical package which has extensive capabilities for forecasting and time series analysis. In this study, we use the automatic modeling capabilities of Forecast Pro by implementing the expert function. The Forecast Pro expert function employs an expert system technology to facilitate automatic ARIMA modeling. Through the iterative process of model identification, parameter estimation and diagnostic checking, Forecast Pro expert produces the "best" linear model fitted to the data at hand. The neural networks is implemented using the Simulator package. Simulator does not have an expert function. Neural network forecasts will then be compared with the forecasts obtained from Forecast Pro.

Before using it in prediction, the network should be tested. This procedure, referred to as validation, is essentially one of validating the information that the network has been abstracted to see if the network can indeed generalize what it has learned to novel exemplars (Baum and Haussler, 1989). Hoptroff, 1993, suggests that validation data should comprise 10-25% of the data available and at least 10 data points. Since the validation data are not used in training, the point of minimum validation RMSE should represent the point where generalization abilities of the model are maximized. We held back around 9% of the data to use for testing the forecasting abilities of the two approaches. We felt that 24 points (out of 277) or two years of data represented a good test especially as the data set used in modeling ended at a turning point in the series.

In sum, we used the actual years for which the data is available and split it into two parts: one large portion of the data (253 observations) is used to build the neural net model while the other much smaller part (24 observations) is used to test the model in the out-of-sample mode by comparing the results of the model to the actual results.

## Results

Since the major purpose of this study is to investigate the modelling and forecasting performance of neural networks, both in-sample (training set) and out-of-sample (test or validation) set results will be dealt with. The focus will be on the out-of-sample analysis because it is the forecasting capability that researchers and practitioners are most interested in. With most traditional forecasting models such as linear regression and Box-Jenkins models, in-sample fitting may not be an issue because of the parametric characteristic of the linear model and the existence of the optimal solution using least square method. For neural network method, however, due to the potential problem of over-fitting, we need to study the conditions under which overfitting may occur. An overfitted model gives good in-sample fit to the training data, yet poor predictive out-of-sample performance. Therefore, the examination of both in-sample and out-of-sample behaviors will provide information on when and how overfitting occurs.

It is expected that as the number of hidden nodes increases, RMSE decreases. This pattern is observed consistently in each level of the input node. This phenomenon is to be expected since the objective in training a neural network is to minimize the SSE or equivalently RMSE. As more hidden nodes are used, the nerual network becomes more "powerful" in modeling the data. Note that too powerful networks are undesirable because they tend to memorize the specific features of individual observations rather than the general pattern in the data, causing poor generalizations. In this study seven neurons were chosen for the hidden layer to minimise the probability of memorization. This is consistent with the fact that the optimum number of hidden layer neurons is determined empirically (Hecht-Nielsen, 1990). Table (3) shows that the RMSE for the neural network model chosen is 0.034 vs RMSE of 0.048 for ARIMA series resulting from "best" ARIMA technique. This implies that forecasts based on neural networks will lead to lesser amount of forecast error.

**Table 3**
**RMSE for Both Models**

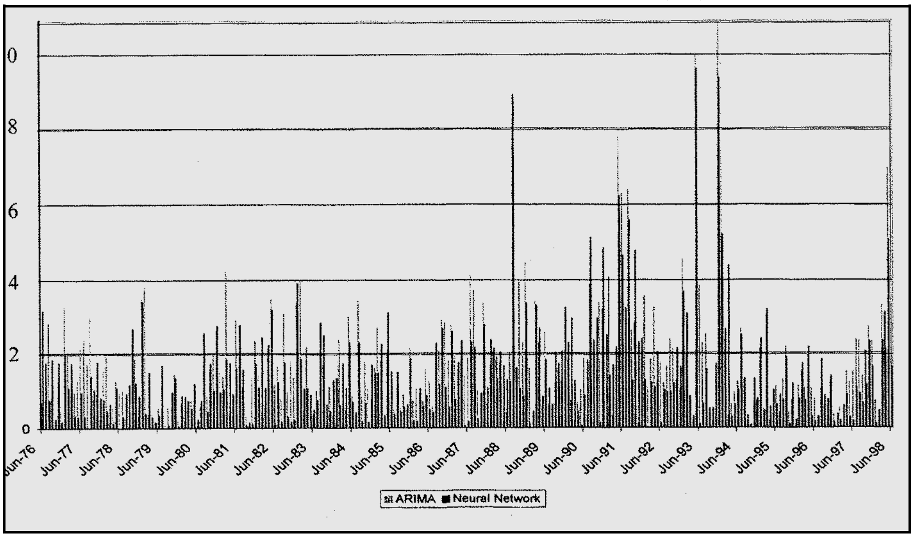
| Model | RMSE |
|---|---|
| Neural network | 0.034 |
| ARIMA | 0.048 |

This is consistent with the literature that compares the performance of neural networks with ARIMA modeling approach (Church and Curram, 1996; Haji and Al-Mahameed, 1999, Schumann, 1993; Tang *et al*, 1991; Zhang and Hu, 1998). Table (4) also shows a comparison of the predictions of neural net and ARIMA on the 24 test data points. The figures in this table confirm those of table (3). This is

**Table 4**
**Actual Figures Vs. ARIMA and NN Forecasts (000 Tons)**

| Actual | ARIMA | NN |
|---|---|---|
| 301020 | 297940.94 | 304160.33 |
| 285880 | 296570.74 | 304660.49 |
| 287190 | 293430.07 | 296080.44 |
| 298200 | 301460.32 | 306010.9 |
| 310200 | 296770.1 | 296010.42 |
| 307710 | 303930.17 | 306230.35 |
| 302010 | 302030.99 | 305880.04 |
| 274990 | 280620.58 | 277110.88 |
| 300080 | 300950.24 | 306220.14 |
| 306340 | 290740.57 | 297250.71 |
| 304020 | 291300.79 | 306980.84 |
| 298920 | 283570.69 | 297120.63 |
| 318010 | 293930.1 | 306940.65 |
| 316380 | 292570.3 | 306900.62 |
| 303820 | 289460.43 | 296920.23 |
| 318630 | 297380.36 | 306770.79 |
| 320440 | 292750.03 | 296850.45 |
| 323560 | 299800.94 | 306710.56 |
| 305440 | 297930.86 | 306710.21 |
| 281750 | 276810.1 | 276980.69 |
| 330400 | 296850.66 | 306670.15 |
| 318260 | 286780.43 | 296730.24 |
| 357390 | 287330.44 | 306610.6 |
| 313380 | 279700.44 | 296710.05 |

**Figure 3**
**Absolute Errors for ARIMA and NN Models (Mt)**




also consistent with figure 3 which shows that the absolute errors for ARIMA series are, in general, higher that that of the neural network.

Figures 4 through 7 show that no pattern is detected in the residuals for both neural net and ARIMA models which suggests that the errors are normally distributed with a mean of zero.

**Figure 4**
**Residuals for ARIMA Series**

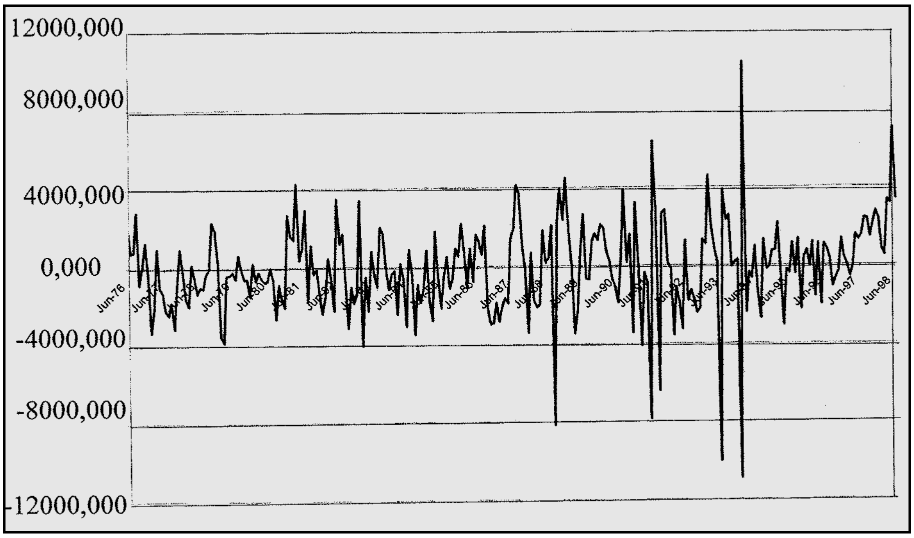


**Figure 5**
**Residuals for Neural Network Series**

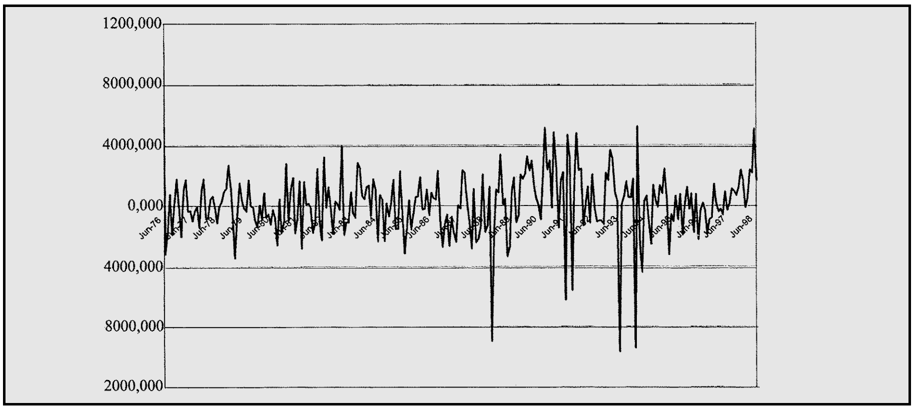



**Figure 6**
**Histogram of ARIMA Series Errors (000 tons)**

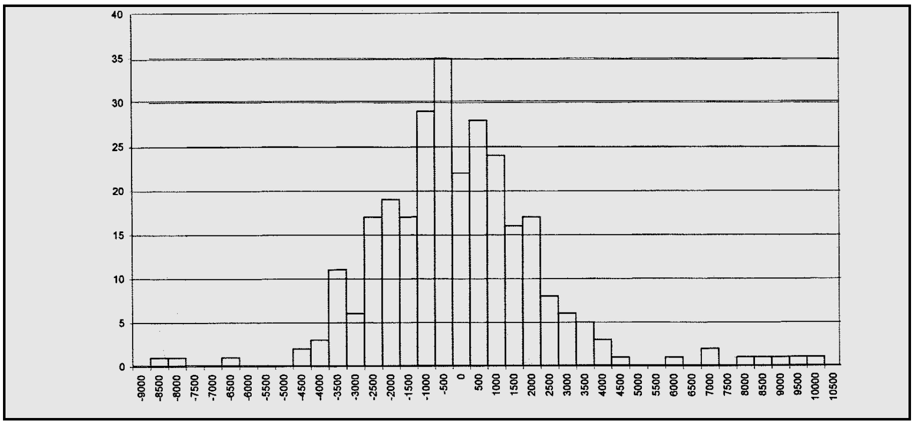



**Figure 7**
**Histogram of the NN Series Errors (000 tons)**

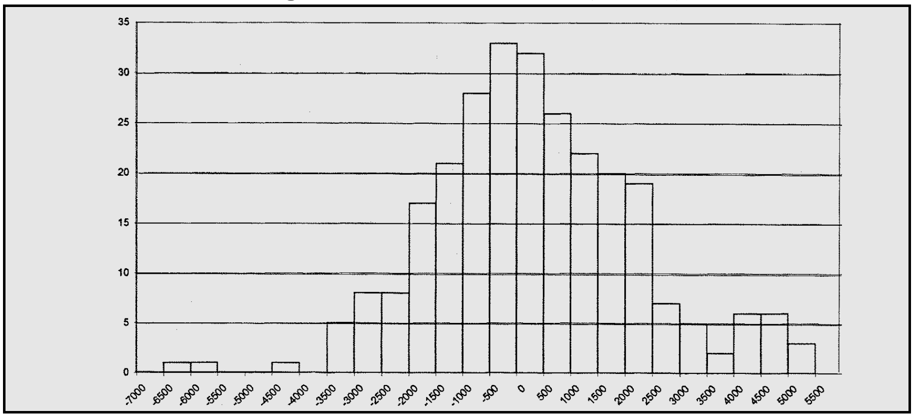
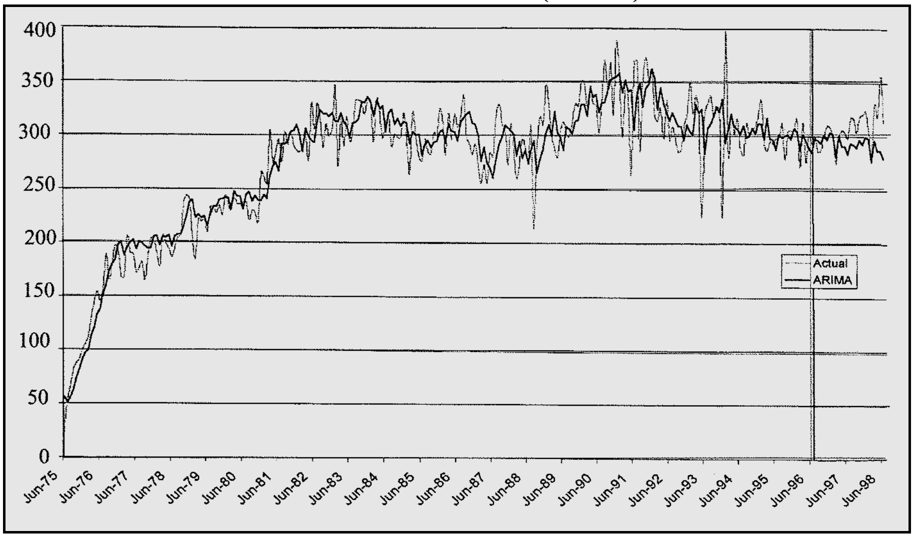


**Figure 8**
**Actual and Forecast in Mt (ARIMA)**




Figures 8 and 9 show the ARIMA and neural net forecasts along with the actual series.

Table (5) compares the out-of-sample neural network forecasting power using RMSE relative to the "best" ARIMA model RMSE (2374.3). The results over a 12 months time horizon shows that the neural networks generally outperform the

**Figure 9**
**Actual and Forecast in Mt (NN)**

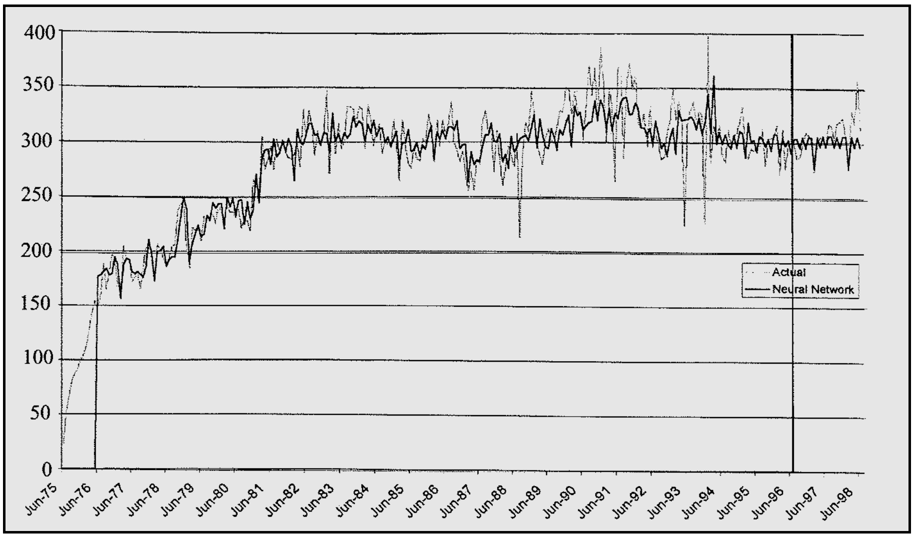


**Table 5**
**Results of Out-of- Sample Forecasts by Neural Network Models**

| Forecast Horizon | RMSE (Not Normalized) |
|---|---|
| 1 | 2073.89 |
| 2 | 2281.82 |
| 3 | 2618.61 |
| 4 | 1990.88 |
| 5 | 1995.89 |
| 6 | 2612.79 |
| 7 | 1988.95 |
| 8 | 1977.57 |
| 9 | 1977.67 |
| 10 | 1965.53 |
| 11 | 1968.64 |
| 12 | 1971.65 |

ARIMA model. The forecasting performance of the neural networks relative to the ARIMA model remains strong throughout the twelve-month forecast horizon and does not appear to deteriorate as the forecast horizon increases. This result is consistent with the fact that neural networks are data-driven, self-adaptive nonlinear methods that do not require specific assumptions about the underlying model. Instead of fitting the data with a pre-specified model form, neural networks let the data itself serve as evidence to support the model's estimation of the underlying generation process. This nonparametric feature makes them quite flexible in modelling real-world phenomena where observations are generally available but the theoretical relationship is not known or testable. It also distinguishes neural network models from traditional linear models and other parametric nonlinear approaches, which are often limited in scope when handling nonlinear or nonstandard problems.

## Policy Implications

In general, this research is of great benefit to public, private, and academic organisations involved in the marine shipping industry. More specifically, the study will be useful for the Suez Canal Authority (SCA) for strategic planning, marketing and business development purposes.

Keeping the Canal profitable is no easy task, given the usual fluctuations in regional and international politics. Forecasting the Canal traffic should help the SCA determine tonnage rates and conduct upgrade schemes to keep the Canal attractive to marine traffic.

Alhough the past 20 years have seen a rise in cargo ships due to route competition, recent changes in the global economy, like the East Asian financial crisis, have hurt Canal traffic. In addition, oil-hungry countries such as the United States have started supplying their energy needs from Nigeria, South America and the Caribbean, forgoing the Canal completely. Forecasting the Suez Canal traffic should also help the SCA in finding ways to increase traffic and boost revenues.

In face of intense competition, the SCA is eyeing a Canal expansion project that it hopes will help attract large ships. At an estimated cost of $ 441m, the expansion will allow 250 000 ton vessels with 75 foot drafts by 2010. This expansion will also widen the canal from 380 to 440 yards, which will allow the passage of 92% of present commercial carriers (Emerging Egypt, 2002).

While these improvements were carried out, the canal has seen a rise in revenues over the past few years. Total receipts for 2000 were $ 1.94 bn, up 10% from 1998. As of the end of 2001, revenues were expected to equal 2000's levels (Please refer to Table 6).

Analysts attribute part of the revenue increase to the rise in world oil prices, as well as to the privatisation of shipping agencies in 1998. Private shipping agencies have made service faster by cutting down on bureaucracy that had previously plagued the industry.

Making services at the Canal more attractive, and thus brining in more ships, should continue with the completion of the East Port Said project. With completion expected in 2003, it is hoped the port will lure more ship traffic through the Canal by offering services to offload containers that would then be carried by feeder ships.

What the immediate future holds is a source of speculation. While plans to widen the canal may lure large super-

**Table 6**
**Suez Canal Traffic and Revenues**

| Canal Traffic | 1999 | 2000 | 2001* |
|---|---|---|---|
| Vessels | 13,490 | 14,141 | 11,823 |
| Revenues ($m) | 1824 | 1943 | 1606 |

* (Jan- Oct)
Source: SCA, 2001

tankers, changes in world oil supply sources might make this a moot point. Already, there are signs that Central Asia could be a major source of oil for Europe and the United States. If this turns out to be the case, pipelines rather than ships might become the primary vehicle for bringing oil to the West. Shipping lines also worry that the Canal is located in an increasingly politically tense region. Ultimately the best way to secure a steady flow of traffic to the Canal is to guarantee stability.

## Summary and Conclusion

Traffic forecasting using neural networks has recently received much attention (e.g. Kirby and Parker, 1994; Vukadinovic *et al*, 1997). In this study, we investigate the Suez Canal traffic forecasting. The number of input nodes and the number of hidden nodes are the experimental neural network factors. Both in sample fitting ability and out-of-sample predictive performance are evaluated with RMSE.

The study shows that the appropriate selection of neural network inputs and architecture structure is critical for the predictive accuracy of traffic data. The purpose of this study is not to provide a clear-cut guidance for selecting an optimal neural network structure for forecasting. Rather, our purpose is to examine the effects of several important neural network factors on model fitting and forecasting behaviors. Obviously, for the forecasting purpose, it is not appropriate to evaluate the neural network capability with the training sample alone. Currently there are no broadly accepted methods for construction of the best predictive model using strictly in-sample training data. The selection of the optimal network architecture should be based on test sample results. The optimal neural network model is the one that gives the best results in the test sample. If this strategy is used for model selection, then a true out-of-sample or validation sample should be employed for model validity purposes. We have also found that the number of input nodes plays an important role in neural network time series forecasting. This is consistent with the theoretical expectation that it is the number of input nodes that determines the (nonlinear) autocorrelation structure. Correct identification of the underlying autocorrelation structure is fundamental in time series forecasting. In addition, neural networks outperform the random walks.

The limitation of this study lies in two aspects. Firstly, only the traffic expressed in tons series is selected for detailed examination, so caution may still need to be exercised for generalization of the results to other traffic data. Second, we investigate only one-step-ahead forecasting strategy. Results for multiple-step forecasting may be different from those obtained from this study. Future research should include the cross validation methodology that can be used to identify the best structure of the neural networks. Robustness of neural networks to the changing structures, or turning points typically associated with traffic series, can be investigated by using multiple training and test samples systematically chosen from the original series.

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# الملخص

## التنبؤ بحركة المرور في قناة السويس باستخدام الشبكات العصبية

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على الرغم من أن قناة السويس هي من أهم الممرات المائية في العالم، فإن الدراسات التي استهدفت التنبؤ بحركة المرور فيها تكاد تكون منعدمة. والدراسة الحالية تستخدم كلاً من نماذج الانحدار الذاتي والمتوسطات المتحركة (نماذج بوكس – جنكنز)، وكذلك نماذج الشبكات العصبية في التنبؤ بحركة المرور في قناة السويس. وقد تزايد في الآونة الأخيرة استخدام الشبكات العصبية في مجال التنبؤ Prediction والتصنيف Classification، وهي من المجالات التي كانت تستخدم فيها نماذج الانحدار وغيرها من الأساليب الإحصائية التقليدية. والنماذج التي توصلت إليها هذه الدراسة تقدم لنا رؤية مفيدة فيما يتعلق بسلوك النقل البحري منذ إعادة افتتاح قناة السويس أمام حركة الملاحة العالمية عام ١٩٧٥ بعد إغلاق دام ثمانية أعوام نتيجة للحروب العربية الإسرائيلية (١٩٦٧ – ١٩٧٣).

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