# Room occupancy rate forecasting: a neural network approach

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**In recent years, neural networks have become popular in the scientific and business fields. In the hotel industry, researchers have recently devoted attention to the application of neural networks to the classification of tourist segments and the prediction of visitor behaviour. However, no previous attempt has been made to incorporate neural networks into hotel occupancy rate forecasting. This paper reports on a study about applying neural networks to the forecasting of room occupancy rates. The significance of this approach was tested with actual data from the Hong Kong hotel industry. Estimated room occupancy rates were compared with actual room occupancy rates. Experimental results indicate that using neural networks to forecast room occupancy rates outperforms multiple regression and naïve extrapolation, two commonly used forecasting approaches.**

**Anonymous reviewers' helpful comments and suggestions are greatly appreciated. This research was supported, in part, by a Hong Kong Polytechnic University Research Grant.**

International Journal of Contemporary Hospitality Management
10/6 [1998] 234–239

[ISSN 0959-6119]

## Introduction

In all categories of measurements, Hong Kong was the most-visited Asian city in the years 1973 to 1995 (Bailey, 1995). Visitors to Hong Kong include, among others, business travellers, individual tourists, tour groups, conference participants, and government officials. In addition to wanting to view the British colony before the political hand-over on 1 July 1997, visitors came to Hong Kong to experience her vibrancy, excitement, cuisine, fashion, and the famous East-meets-West culture (Go *et al.*, 1994). Recently, the Hong Kong Tourist Association has promoted Hong Kong as a city where "Wonders Never Cease". Table I illustrates the growth of the Hong Kong hotel and tourism industry in the period 1973 to 1995 inclusive (Hong Kong Tourist Association, 1974-1995).

As depicted in Table I, Hong Kong has been experiencing rapid growth in the hotel and tourism industry. The number of visitors in Hong Kong in 1995 was about eight times the corresponding number in 1973. Additionally, the number of hotels and hotel rooms increased significantly over the period. Such a significant number of hotel rooms places a considerable pressure on hotel managers to manage their capacity effectively. This observation, coupled with the increase in the average number of rooms per hotel property, necessitates the application of modern management techniques and the latest technology in order for hotels in Hong Kong to sustain their competitiveness in the Asia-Pacific hotel market.

In general, hotel businesses are profitable with an average room occupancy rate over 60 percent. To demonstrate, in an earlier study of resort destinations, Stoner reported that an average room occupancy rate of 68 percent would make a specific location desirable for Hyatt Hotels, and other global developers (Stoner, 1987). Similarly, Teo claimed that Kuala Lumpur enjoyed a 70 percent hotel occupancy rate (Teo, 1992). Compared with other cities, hotels in Hong Kong maintain a relatively high room occupancy rate. On average, room occupancy rate is above 80 percent in the study period as specified in Table I. This is likely to motivate investors to maintain or increase their investment in Hong Kong hotels. A more accurate forecasting of room occupancy rates would facilitate strategic planning and enhance the decision-making procedures of hotel management companies. The primary objective of this research was to investigate the feasibility of incorporating a neural network (also known as an artificial neural network), computer software that mimics the human brain in order to deduce or learn from a database, to forecast room occupancy rates for the Hong Kong hotel industry. An accurate room occupancy rate forecast would assist hotel managers, especially managers in budget-constrained hotels, in their strategic, tactical, and operational planning. Another objective of this research work was to make an attempt to keep the hotel and tourism industry at the leading edge by employing new computing technology.

Having introduced the research background in the previous paragraphs, the remaining sections of this paper are organized as follows. First, there is an overview section of neural networks. In this overview section, the theoretical foundation of a neural network is examined. In particular, the use of neural networks as a forecasting tool for business applications is analyzed. Based on the theoretical description, a neural network is used to create a forecasting model for room occupancy rates for the Hong Kong hotel industry. The modelling process is discussed in the next section. An experimental section then follows, which presents the room occupancy rate forecasting results. Forecasting quality is measured in mean percentage error, acceptable output percentage, and normalized cross-correlation. The results forecast by the neural network are then compared with the corresponding values obtained from multiple regression and naïve extrapolation, two commonly used forecasting methods used by top managers of all hotels listed on the Hong Kong Stock Exchange (Lam, 1996). An analysis section is then presented, which covers the research findings and the applicability of the neural network to room occupancy rates for the Hong Kong hotel industry. Finally, the conclusion section analyzes the significance of this

International Journal of Contemporary Hospitality Management
10/6 [1998] 234–239

**Table I**
An overview of the Hong Kong hotel and tourism industry

| Year | Number of tourists | Average stay length | Number of hotels | Number of rooms | Tourists per room | Percentage of hotel accommodation (%) | Room occupancy rate (%) |
|---|---|---|---|---|---|---|---|
| **1973** | 1,291,950 | 3.5 | 54 | 11,316 | 114.170 | 89.1 | 77.0 |
| **1974** | 1,295,462 | 3.6 | 55 | 13,190 | 98.220 | 89.5 | 71.0 |
| **1975** | 1,300,836 | 3.7 | 53 | 13,448 | 96.731 | 90.0 | 67.0 |
| **1976** | 1,559,977 | 3.8 | 52 | 13,347 | 116.880 | 91.3 | 79.0 |
| **1977** | 1,755,669 | 3.8 | 50 | 13,800 | 127.222 | 90.1 | 85.0 |
| **1978** | 2,054,739 | 3.9 | 49 | 14,168 | 145.027 | 89.4 | 89.0 |
| **1979** | 2,213,209 | 3.7 | 46 | 14,363 | 154.091 | 89.4 | 91.0 |
| **1980** | 2,301,473 | 3.6 | 46 | 14,989 | 153.544 | 87.6 | 87.0 |
| **1981** | 2,535,203 | 3.6 | 47 | 16,323 | 155.315 | 87.2 | 87.0 |
| **1982** | 2,609,100 | 3.6 | 47 | 17,415 | 149.820 | 86.6 | 82.0 |
| **1983** | 2,775,014 | 3.6 | 48 | 17,518 | 158.410 | 86.0 | 83.0 |
| **1984** | 3,151,672 | 3.6 | 50 | 17,979 | 175.297 | 85.0 | 89.0 |
| **1985** | 3,443,173 | 3.6 | 51 | 18,180 | 189.393 | 84.0 | 88.0 |
| **1986** | 3,733,347 | 3.5 | 57 | 20,230 | 184.545 | 82.0 | 85.0 |
| **1987** | 4,501,889 | 3.5 | 56 | 21,022 | 214.151 | 81.0 | 90.0 |
| **1988** | 5,589,292 | 3.4 | 65 | 22,882 | 244.266 | 82.0 | 92.0 |
| **1989** | 5,361,170 | 3.4 | 69 | 27,031 | 198.334 | 84.0 | 79.0 |
| **1990** | 5,932,854 | 3.3 | 75 | 28,146 | 210.789 | 85.0 | 79.0 |
| **1991** | 6,032,081 | 3.4 | 82 | 31,163 | 193.565 | 84.0 | 75.0 |
| **1992** | 6,986,163 | 3.4 | 86 | 33,534 | 208.331 | 88.0 | 82.0 |
| **1993** | 8,937,500 | 3.8 | 88 | 34,044 | 262.528 | 84.0 | 87.0 |
| **1994** | 9,331,156 | 3.9 | 85 | 33,490 | 278.625 | 80.0 | 85.0 |
| **1995** | 10,199,994 | 3.9 | 86 | 33,052 | 308.604 | 78.0 | 85.0 |

research and suggests future research possibilities.

## An overview of neural networks

A neural network is best described as an intelligent computer system that mimics the processing capabilities of the human brain (Law, 1996). Neural networks are an information technology capable of representing knowledge based on massive parallel processing (rapid retrieval of a large quantity of information) and pattern recognition based on past experience or examples (Wang and Sun, 1996). The pattern recognition ability of a neural network makes it a superb classification and forecasting tool in business applications. To illustrate, Lenard *et al.* (1995) used the generalized reduced gradient optimizer (a nonlinear constrained optimization program based on the generalized reduced gradient method) for neural network learning to assist an auditor's judgment on unstructured tasks. Experimental results in Lenard *et al.*'s study showed that the neural network model achieved a 95 percent prediction accuracy rate, and this outperformed the logit procedure (a logistic response function which describes a binary dependent variable containing qualitative outcomes) significantly. Similarly, Jain and Nag (1995)applied neural networks to model initial public offering prices and obtained significant economic benefits. Moreover, Markham and Ragsdale (1995) confirmed that neural networks outperform Mahalanobis distance measures (a standard statistical classification) in business classifications.

A neural network consists of an input layer, an output layer, and usually one or more hidden layers. Each of these layers contains nodes, and these nodes are connected to nodes at adjacent layer(s). Figure 1 demonstrates a typical neural network with three layers.

Each node in a neural network is a processing unit that contains a weight and a summation function. A weight returns a mathematical value for the relative strength of connections to transfer data from one layer to another layer; whereas a summation function computes the weighted sum of all input elements entering a processing unit. Nodes in the input layer represent variables that resemble the original problem. For instance, to determine a person's credit rating, a financial institution needs information about that person's income level, education background,

International Journal of Contemporary Hospitality Management
10/6 [1998] 234–239

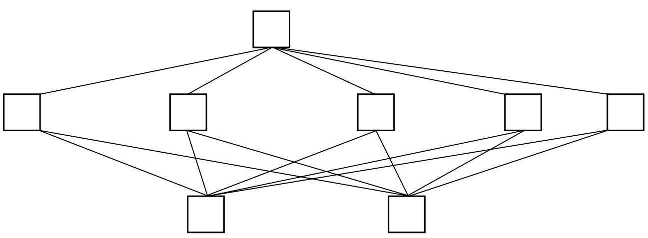
and home ownership status as the essential input variables. The output of a neural network is the solution to a problem. To demonstrate, a numeric value from the output node is used to represent the credit rating of an individual loan applicant.

A neural network learns from training data to discover patterns representing input and output variables. Usually, the process of learning involves the following stages:

1 Assign random numbers into the weights.
2 For every element in the training set (a set of sample observations used to develop the pattern or relationship among the observations), calculate output using the summation functions embedded in the nodes.
3 Compare computed output with observed values.
4 Adjust the weights and repeat steps 2 and 3 if the result from step 3 is not less than a threshold value.
5 Repeat the above steps for other elements in the training set.

What makes a neural network superior to traditional statistical methods in forecasting is that a neural network is better able to recognize the high level features, such as the intra-correlation or serial correlation, of a training set. Furthermore, a neural network has been demonstrated to outperform standard statistical models in forecasting with a small-sized training set and a high level of white noise (random errors in the samples) (Pattie and Snyder, 1996). This feature was particularly useful for forecasting the room occupancy rates in this research, as the number of samples in the training set was relatively small due to data availability. An additional advantage of applying a neural network to forecast is that a neural network can capture the non-linearity of samples in the training set (Wang and Sun, 1996). The non-linear factor handling ability of a neural network distinguishes itself from other time series models. Pattie and Snyder claimed, with substantiation, that using a neural network to forecast non-linear tourist behavior could achieve a lower mean absolute percentage error, lower cumulative relative absolute error, and lower root mean square error than linear trend, single exponential smoothing, Box-Jenkins, or the naïve extrapolation models (Pattie and Snyder, 1996). Additionally, the neural network developed by Lu *et al.* significantly outperformed loglinear and logit models (with a lower sum of square error and a higher accuracy rate of prediction) to improve franchising decision making (Lu *et al.*, 1996). Similarly, Mazanec demonstrated that a neural network is superior to discriminant analysis function in classifying tourists into market segments based on a set of non-linear demographic, socioeconomic, and behavioral variables (Mazanec, 1992).

**Figure 1**
A neural network model




## A room occupancy rate forecasting model

In view of the notable forecasting performance of a neural network, this research attempts to model the room occupancy rate forecast using a neural network. To date, there exists no published work that makes such an attempt. This is particularly true in the context of the Hong Kong hotel industry. This study adopts the data from Table I for training and testing. In order to eliminate the temporal effect, among the 23 sample entries, 13 were randomly chosen to form the training set, and the rest were used for forecast testing (validation). The input variables considered in this study are listed below:

1 NoT: number of tourists.
2 ASL: average stay length in number of days.
3 NoH: number of hotels.
4 NoR: number of hotel rooms.
5 TpR: tourists per room.
6 PHA: percentage of hotel accommodation.

The six input variables for constructing the neural network in this study were used because of their possible influence on hotel room occupancy rates in Hong Kong. Viewing from a macro-economic point, these input variables relate to the demand and supply of hotels and hotel rooms. In Hong Kong, 97 percent of hotel business was from visitors (Hong Kong Tourist Association, 1995). Therefore, the chosen input variables could largely affect room occupancy rate in Hong Kong. The NoT, ASL and PHA variables are demand indicators, and hence potential profits. PHA is a measure of percentage of tourists who stayed in hotels instead of homes of their relatives or friends. The NoH and NoR variables are supply indicators. The TpR variable is a measure of demand-to-supply ratio that has a direct relationship with room occupancy rates.

The output variable used in this research is ROR, which represents the room occupancy rate. Figure 2 shows the neural network, with a hidden layer of eight nodes, which was employed in this research to forecast the room occupancy rates for Hong Kong hotels.

A computer program was implemented using AiNet version 1.1 for the neural network model presented in Figure 2, with six input nodes (dependent variables), eight nodes in the hidden layer for rapid convergence, and one output node (independent variable). The program was executed on a Pentium 133 computer running Windows 3.1, using the data from training set and testing set. Experimental results are presented in the next section.

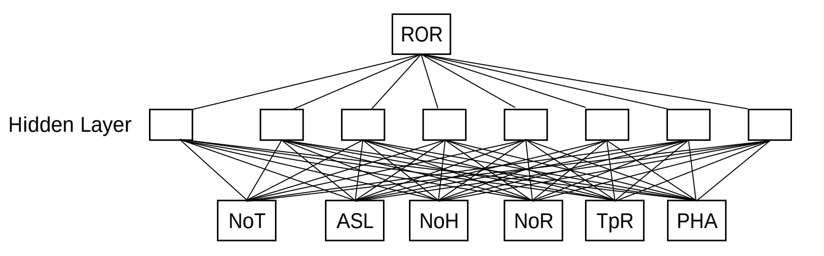
## Experimental results

Multiple regression and naïve extrapolation, two commonly used forecasting models (Au *et al.*, 1996; Lam, 1996), were employed to forecast room occupancy rates based on the training set. Table II reveals the experimental results of the three different models, and Figure 3 provides a graphical presentation of these results.

The output of the three forecasting models is based on mean percentage error ($\varepsilon$), acceptable output percentage ($Z$) (i.e. in the permissible range), and normalized cross-correlation ($R$). $\varepsilon$ is a relative measurement used for comparison across the testing data because it is easy to interpret, independent of scale, reliable and valid. $Z$ is used as a relative measurement for acceptance level. After consultations with local hotel executives, $Z$ was assigned a value of 5 percent. $R$ is a measure of the closeness of the observed and estimated occupancy rates. Each of these measurements is defined next:

$$\varepsilon = \frac{\sum_{i=1}^{n} \frac{|Xi - Yi|}{Yi}}{n} * 100\%$$

**Figure 2**
A room occupancy rate neural network model




$$z = \frac{\sum_{i=1}^{n} i}{n} * 100\% \text{ for } \begin{cases} i = 1 \ldots \text{ if } \frac{|Xi - Yi|}{Yi} \leq 5\% \\ i = 0, \ldots \text{ otherwise} \end{cases}$$

$$R = \frac{\sum_{i=1}^{n} (Xi * Yi)}{\left[\sum_{i=1}^{n} (Xi)^2 * \sum_{i=1}^{n} (Yi)^2\right]^{0.5}}$$

Where $Xi$ and $Yi$ represent the estimated and actual occupancy rates for $i = 1, \ldots, 10$, respectively. In this research, $n = 10$. Values of $\varepsilon$, $Z$, and $R$ are presented in Table III.

Data in Table IV, representing the relative percentage error of the three forecasting models, are used to test for the statistical significance between the group means. Two Mann-Whitney U tests were conducted, and the values of U statistic are presented in Table V.

## Analysis

It can be observed from Table III that the estimated room occupancy rates from a neural network are very close to the actual values. In other words, the forecasting output from a neural network is accurate, with an acceptable amount of error. The low mean percentage error indicates that the deviations between the estimated values derived by the neural network and the actual values are very small. Hotels in Hong Kong can tolerate a 5 percent difference in room occupancy rates. Therefore, a neural network succeeds in achieving 80 percent of output within the acceptable range. Furthermore, the normalized cross-correlation is almost 1. Again, this demonstrates the close relationship between the estimated results and the actual hotel data.

As indicated in Table III, a neural network outperforms the multiple regression and naive extrapolation models in terms of mean percentage error, acceptable output percentage, and normalized cross-correlation. Also, the non-parametric Mann-Whitney U statistic values in Table V were both significant at the 0.05 level of a one-tailed test, meaning that a neural network outperforms both multiple regression and naïve extrapolation models in room occupancy rate forecasting.

## Conclusions

In this paper, the procedures of room occupancy rate forecasting for the Hong Kong hotel industry, using a neural network, are presented. Officially published data were

**Table II**
Experimental results of room occupancy rates

| Actual occupancy rate (%) | Estimated occupancy rate (%) (multiple regression) | Estimated occupancy rate (%) (naïve extrapolation) | Estimated occupancy rate (%) (neural network) |
|---|---|---|---|
| 79.0 | 52.30 | 83.38 | 79.00 |
| 89.0 | 85.99 | 82.92 | 88.00 |
| 71.0 | 68.59 | 83.85 | 70.11 |
| 83.0 | 57.68 | 84.15 | 88.97 |
| 85.0 | 89.15 | 83.62 | 85.00 |
| 82.0 | 80.13 | 83.31 | 83.51 |
| 87.0 | 85.79 | 82.62 | 82.86 |
| 92.0 | 95.99 | 83.00 | 85.13 |
| 75.0 | 94.59 | 83.31 | 79.04 |
| 87.0 | 92.05 | 82.54 | 84.27 |

**Figure 3**
Graphical presentation of forecasting results

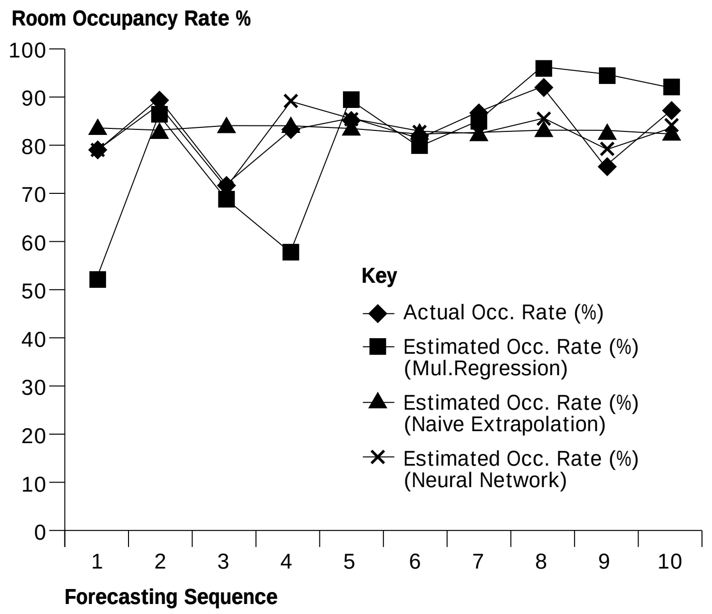



**Table III**
A comparison of forecasting models

| | $\varepsilon$ | $z$ | $R$ |
|---|---|---|---|
| **Neural network** | 3.1 | 80 | 0.999 |
| **Multiple regression** | 12.8 | 50 | 0.996 |
| **Naïve extrapolation** | 6.7 | 50 | 0.997 |

**Table IV**
Relative percentage error in the validation samples

| Sample | Neural network (%) | Multiple regression (%) | Naïve extrapolation (%) |
|---|---|---|---|
| **1** | 0.0 | 34.0 | 6.0 |
| **2** | 1.0 | 3.0 | 7.0 |
| **3** | 1.0 | 3.0 | 18.0 |
| **4** | 7.0 | 31.0 | 1.0 |
| **5** | 0.0 | 5.0 | 2.0 |
| **6** | 2.0 | 2.0 | 2.0 |
| **7** | 5.0 | 14.0 | 5.0 |
| **8** | 7.0 | 4.0 | 10.0 |
| **9** | 5.0 | 26.0 | 11.0 |
| **10** | 3.0 | 5.8 | 5.0 |
| **Average** | 3.1 | 12.78 | 6.7 |

**Table V**
Tests for differences in the relative percentage error

| Comparison | Mann-Whitney *U* value[a] |
|---|---|
| **Neural network vs multiple regression** | 23.5 |
| **Neural network vs naïve extrapolation** | 27 |

**Note:**
[a] Both *U* values are significant at $\alpha = 0.05$

divided into a training data set and a testing data set. The input nodes of the neural network held independent variables for factors that determine the room occupancy rate (dependent variable). The output node consisted of the room occupancy rates for Hong Kong hotels. The output of the neural network model demonstrated forecasting efficiency by making comparisons with actual data. In this research, the forecasting efficiency of a neural network prevailed over multiple regression and naïve extrapolation. This shows the feasibility of incorporating a neural network forecasting model into the actual hotel environment in Hong Kong. Forecasting is a major requirement of planning (Athiyaman and Robertson, 1992). Practitioners and policy makers may confidently apply neural networks, as an alternative to the traditional time-series and economic forecasting models, for their planning activities.

International Journal of Contemporary Hospitality Management
10/6 [1998] 234–239

This research was an initial attempt to model room occupancy rates for the Hong Kong hotel industry. The research work, albeit limited in scope, is applicable to the Hong Kong hotel industry. Currently, the Hong Kong hotel and tourism industry is facing the challenges of a changing global tourist market, competition from nearby cities, and the political hand-over in July 1997. Managers are reluctant to make incorrect business decisions. So they will benefit from better business planning and decision making.

A future research possibility is to include more dependent variables to determine the room occupancy rate forecasting efficiency of a neural network. For instance, it is natural to believe that government policies, weather conditions, and national wealth can play an important role in determining tourist arrivals, leading to a significant change in room occupancy rates. However, some factors such as government policies and weather conditions are dynamic in a continuous fashion. Hence, it could be difficult to provide a commonly acceptable measurement for these factors.

Another potential area for future research would be to perform the room occupancy rate forecast, using a neural network, for other cities. Room occupancy rates in Hong Kong are stable and consistently high compared with other cities. It would be worthwhile to investigate whether a neural network can maintain such a high accuracy to forecast room occupancy rates in cities with non-stable or low room occupancy rates. Again, a room occupancy rate forecasting model with a low estimation error would help hotel managers make operational, tactical, and strategic decisions.

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